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Technological adoption and Firm Resilience: Understanding the Impact of New Digital Technologies

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Technological adoption and Firm Resilience: Understanding the Impact of New Digital Technologies

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ABSTRACT

This study investigates the impact of new digital technologies on the resilience of firms to external shocks. Using rare comprehensive data on both the adoption of single and multiple new digital technologies, we employ a Difference-in-Differences methodology with propensity score matching to evaluate how digitalization influenced firms' ability to withstand the COVID-19 crisis. We isolate the effects of adopting 1) a single technology, 2) multiple technologies (the breadth of adoption), and 3) technologies that are complementary to one another. The findings provide novel insights into how firms can shape their investments in new digital technologies to increase the benefits of digitalization, and enhance their ability to navigate future crises.

Keywords: digital technologies, resilience, technological complementarities

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1 Introduction

Shocks, crises and disruptive events, such as the financial crisis of 2008, the COVID-19 pandemic or extreme events induced by climate change, often have devastating effects on business performance. Organizational resilience, defined as the firm's ability to minimize falls in performance caused by disruptive events (Dimitriadis, 2021; Williams et al., 2017), has long been recognised as an important question in the field of strategy (Levinthal and March, 1981), but recent shocks have brought it back with urgency under the spotlight. Resilience involves a complex interplay of organizational capabilities, strategies and governance structures, which are path-dependent and idiosyncratic. On the one hand, resilience is specific to industry and market contexts, and business decisions capable of making firms resilient during a period of crisis or distress depend on their exposure and vulnerability to a common shock (Dormady et al., 2019). On the other hand, specific resources, assets, and strategic choices are known to play a crucial role in building resilience, and innovation features prominently among them. Innovative firms are better equipped to adapt to changes and sustain their competitive advantage, as a necessary precondition for resilience (Reinmoeller and van Baardwijk, 2005; Lien and Timmermans, 2024; de Carvalho et al., 2016; Hamel and Välikangas, 2003). Through the introduction of social distancing, restrictions to production, operational and commercial activities, limitations to the movement of goods and people and the rise of remote working, the COVID-19 pandemic has posed formidable economic challenges, and highlighted - arguably above all others - the importance of a specific type of innovation: digitalization (Bai et al., 2021). The literature contains rich evidence on the positive impact of new digital technologies on firm performance, even though different technologies affect various areas of strategic decision-making and influence performance from different angles (Hamel and Välikangas, 2003; Cirillo et al., 2023; de Carvalho et al., 2016). However, the COVID-19 crisis put to the clearest possible test the digital capabilities of firms, and it is no surprise that the pandemic determined a significant increase in the rate of adoption of new digital technologies Calvino et al. (2024). Despite the increasing attention dedicated to digitalization during the COVID-19 pandemic, significant research gaps remain (Iftikhar et al., 2021). Most studies have focused on analyses at the regional or industry level, often lacking essential information on the adoption decisions of individual firms, and their nature and composition (Abidi et al., 2022; Copestake et al., 2024). Crucially, the few studies that have explored this recent wave of digitalization typically concentrated on the contingent adoption of technologies during the pandemic, rather than assessing prior technology adoption decisions and the digital absorptive capacity of firms. However, interestingly, Calvino et al. (2024) in examining the relationship between pre-crisis firm-level factors (both external and internal, such as access to finance or external technological spillovers and digitalization levels or workforce skills), find that firms already equipped with digital infrastructure and with higher digital capabilities were more able to advance their digitalisation over the pandemics, that in turn influenced their capacity to react and adapt to the crisis. Moreover, many of the existing studies relied on surveys conducted during the pandemic which tended to have limited sample sizes and industrial coverage, as well as very general definitions of digitalization (Bianco et al., 2023, Rapaccini et al., 2020, Costa et al., 2022). Data limitations also implied the use of unsatisfactory identification strategies and the production of limited evidence on the effects of different digital technologies, and the specific role of technological interdependencies and complementarities in fostering organizational resilience.

The paper addresses these gaps in the literature by building a comprehensive theoretical framework on the relationship between digitalization and resilience, and leveraging detailed data provided by the Italian National Institute of Statistics (Istat) on the adoption of Internet of Things (IoT), 3D printing, Robotics, Cloud Computing, Big Data Analytics, Augmented Reality, IT security, E-commerce, Apps and Computerized or Sensor-Managed Interconnected goods (CSMI goods) by Italian firms in 2016 and 2017. We use a Difference-in-Differences approach with Propensity Score Matching to evaluate the effect of prior technological adoption and technological complementarities on firm resilience to the COVID-19 crisis. Previous empirical evidence suggests that the wave of digitalization observed across firms in 2020 largely represented an upgrade of existing digital capabilities rather than a widespread first-time adoption of new technologies (Calvino et al., 2024). This insight strengthens our analytical framework, allowing us to more precisely assess the role of prior digital adoption in mitigating the effects of the crisis. The dimensions of resilience we explore are productivity, turnover and employment. Our findings indicate that (pre-crisis) digitalization significantly enhanced firms' ability to mitigate turnover, employment and productivity losses. This effect is evident for firms that adopted bundles of two or more digital technologies. However, the effects of different technologies present strong sectoral heterogeneity.

The paper is organized as follows: the next section introduces the relevant literature and sets our research hypotheses. In Section 3, we describe the data and context of our contribution, and outline the empirical strategy. In Section 4 and 5 we present the result and the heterogeneity analyses. Section 6 describes the Robustness analyses conducted and Section 7 draws the paper to a close.

2 Theoretical framework and hypotheses

2.1 Resilience

The term Resilience stems from the Latin word "*resilio*", which means "to rebound, spring back" (Alexander, 2013). In the field of management and organization studies, the concept of resilience has been used to describe organizations, systems, or individuals that are able to react to and recover from duress or exogenous disturbances with minimal effects on their stability and functioning (Linnenluecke, 2015). Building on this line of research, resilience can be defined as a firm's ability to minimize a decline in performance caused by disruptive events (Dimitriadis, 2021; Williams et al., 2017). Existing research has emphasized two sources of resilience: slack resources and adaptability (Sutcliffe and Vogus, 2003; Dimitriadis, 2021). Slack resources refer to financial reserves that the organization can save during periods of growth and that can be used during economic crises to sustain its performance (George, 2005). These resources provide flexibility to the organization, allowing it to change strategy or absorb cash flow problems until the crisis is over. Adaptability refers instead to an organization's ability to notice disruption, make sense of it and work with or around it (Weick, 1993). Usually, it entails the deployment of specific routines and best practices (Williams et al., 2017). A fundamental component of adaptability is innovation and, increasingly, digitalization, as necessary conditions to withstand exogenous shocks (Reinmoeller and van Baardwijk, 2005; Lien and Timmermans, 2024; de Carvalho et al., 2016; Hamel and Välikangas, 2003).

2.2 The effect of digitalization on resilience

The impact of digitalization on long-run growth and innovation has been extensively studied, but the significance of digital technologies in the context of economic downturns acquired new meaning during the COVID-19 pandemic. Building on the concept of resilience, digital technologies can enhance firms' ability to withstand crises by bolstering their stability and their competitive advantage (Conz and Magnani, 2020; Hillmann and Guenther, 2021). Digital technologies can have a significant impact on employment, affecting both the quantity and type of jobs available. The adoption of digital technologies is influencing hiring and firing decisions, the nature of employment contracts, and the human capital requirements of organizations, despite the presence of significant heterogeneity by firm size (Bisio et al., 2023). In addition, digital technologies can facilitate innovation (Crespo et al., 2023). There is a growing literature on innovation in times of recession, which has focused on whether innovation is a pro- or counter-cyclical phenomenon. This literature argues that innovation would be procyclical in the sense that the majority of the firms cut their expenses in innovation in recessionary contexts and only a small minority of firms continue to innovate or even increase their efforts (Antonioli and Montresor, 2021; Archibugi et al., 2013; Cefis, 2003). Lien and Timmermans (2024) define this type of innovation "crisis-induced innovation". Indeed, the majority of firms innovating during a recession do not aim at the introduction of radical innovations, but rather target the "creative adoption" (Antonelli, 2006) of technological solutions that are new to the firm, as opposed to new to the market. Seen in this light, innovation during a recession is faster than innovation in normal times, less ambitious and more necessity-based in terms of strategic objectives. Digitalization processes that took place during the pandemic can be qualified as "crisi-induced innovation". It can be argued, however, that new technologies unleash their potential when they have been fully absorbed by the firm, and work jointly with the required complementary skills and organizational designs. It is therefore adoption before a crisis that may allow firms to use these technologies to innovate and improve their performance during the crisis period relative to non-adopters (Crespo et al., 2023). The implementation of new digital technologies allows firms to collect customers' feedback, better identify risk factors, and gain insights from the data collected on the production processes, so that the firms can identify more efficient business practices and strategies to react to crisis (Pereira et al., 2022; Ladeira et al., 2019). Furthermore, efficiency gains are produced once digital technologies' adoption has been integrated across different areas of production and management (Ardito et al., 2021), thus also producing a business environment more alert to market signals and more prone to experimentation and adaptation (Arias-Pérez and Vélez-Jaramillo, 2022).

Against the backdrop of the COVID-19 crisis, where the survival of organizations and their ability to continue functioning during the pandemic were closely tied to their capacity to minimize physical contact, adhere to social distancing guidelines, adapt to trade and supply-side constraints, and transition to remote work, the effectiveness of digitalization depended on the deep embeddedness of new technologies in the organization's routines and processes. Based on this conjectures, we formulate the following hypothesis:

Hypothesis 1*: Prior adopters of any single digital technology are more resilient than non-adopters.*

2.3 The breadth of technology adoption

The advent of new digital technologies has significantly impacted firm performance, as we have argued; yet the new digitalization wave does not involve a single technology, but rather multiple technologies. The literature has predominantly focused on the impact of Robotics and, more recently, on Artificial Intelligence. The introduction of robots and, with them, the automation of production processes foster firm productivity compared to non-adopting competitors (Koch et al., 2021). The employment effects of automation are still debated, with some findings suggesting a decrease in firms' employment and others an increase, concentrated in high-skilled jobs (see among others Acemoglu et al., 2020; Domini et al., 2022). Other digital technologies can also deeply affect firm performance (Martinelli et al., 2021). While the adoption of robotics, and the advantages related to it, are mainly concentrated in specific manufacturing sectors, the other new digital technologies have a broader range of applications and so are interesting for a wider set of industries (Ciarli et al., 2021; Mondolo, 2022). 3D printing enhances production flexibility, reduces production time, and allows for experimentation, for example, new and potentially interesting materials. It also enables better alignment between supply and demand (Kamble et al., 2018), allowing firms to optimize inventory management processes, and upgrade production techniques in search of greater efficiency (Hofmann and Rüsch, 2017). The Internet of Things (IoT) allows production items and components to be connected to the environment and interconnected with one another through sensors (Xia et al., 2012), while collecting real-time data as they interact. The adoption of IoT technology has grown significantly over the last few years, and was expected to generate productivity gains ranging between 7% and 15% (Tang et al., 2018). Big Data Analytics allows firms to extract insights from the data produced throughout production and consumption processes alike, and is used to adapt production to the feedback received by uncovering hidden patterns, complex correlations and market trends. The use of big data analytics increases both sales and productivity, helping the firm to make informed business decisions, although significant heterogeneity has been detected between firms of different sizes (Ardito et al., 2018; Wamba et al., 2017). More specifically, large firms seem to register a higher impact of big data analytics on their overall productivity, while smaller firms tend to grow their sales (Conti et al., 2023). Finally, to complete the range of possible adoption choices, there is IT security. Even though this is a technology with a relatively long history in ICT, the multiplication of digital platforms, increases in their functionality, and the proliferation of threats, have made cybersecurity an essential component of new digital technologies, with the difficult task of balancing off efficiency gains with the need for additional controls in a firm's information systems, particularly with respect to the growing amount of data managed by businesses (Barlow et al., 2013; Chen et al., 2017; Whitman and Mattord, 2019). Considering the heterogeneous nature of the different technologies, and the fact that general-purpose technologies such as digital technologies tend to display strong spillover effects, we posit that the breadth of technology adoption choices may be especially beneficial for firm performance during a crisis. We therefore hypothesize that:

Hypothesis 2: *The combined adoption of two or more new digital technologies increases firm resilience compared to the adoption of a single technology.*

2.4 Technological complementarities

Digital technologies, especially those associated with Industry 4.0, are highly interconnected and interdependent and organizations could obtain strong benefits by leveraging the synergies among these technologies (Tortorella et al., 2019). New digital technologies enable extensive changes in established production processes, requiring a reorganization of work, spaces and production methods. Unlike many previous technological developments, these new digital technologies can be successfully adopted across a wide range of industries, improving the performance not only of the manufacturing sector but also of the service sector (Brynjolfsson and McAfee, 2014). For instance, technologies like Robotics and 3D printing target similar aspects of the production process, aiming to automate production with a particular focus on the manufacturing sector. However, robots have now been deployed also in some service sectors, from customer care to healthcare (Wirtz et al., 2021). There are also technologies, like IT security, that are transversal to different sectors and fundamental for the implementation of many other technologies, especially those involved with data collection, storage and analysis. Indeed, the possibility of hierarchical patterns in the adoption of digital technologies — where more sophisticated technologies are adopted only after more basic ones have been installed and well integrated within the firm — has been recognized (Zolas et al., 2020). Related to this, recent empirical evidence (Cho et al., 2023) points to the strategical adoption of specific NDTs, such as those that rely on large amounts of data (e.g., Big Data Analytics) and those that generate large volumes of data themselves (e.g., IoT), along with technologies that enable data storage and information management (e.g., Cloud Computing). Moreover, it has also been found that various technologies can enhance different or the same stages of production, and when combined, they can significantly improve overall performance. For example, integrating the Internet of Things (IoT) with Cloud computing and Big Data Analytics enables firms to extract valuable insights from their production and sales processes (Battaglia et al., 2023). However, there is a lack of empirical research evaluating not only the breadth of technology adoption, but also specific technological complementarities, particularly with regard to their effects on firm performance (Battaglia et al., 2023). This gap becomes even more pronounced when considering the concept of resilience, which shifts the focus from growth to the ability to withstand crises or unexpected events.

Following the classification of technologies operationalized by Balsmeier and Woerter (2019), we consider the complementarities between two groups of technologies: machine-based and non-machine-based technologies. The first group includes complex new digital technologies, whose adoption is expected to drive the current industrial revolution and profoundly affect the economic landscape and the workforce. Non-machine-based digital technologies include instead those that do not imply the introduction of physical objects through large hardware outlays, but mainly consist of software solutions. Machine-based technologies can be used in association with advanced data and computation technologies. However, contrary to non-machine-based technologies, they are capital-intensive, require more high-skilled labor and are profitable only if they successfully allow the firm to produce at lower costs or to increase the quality of final products. Following the definition of Balsmeier and Woerter (2019), machine-based technologies include IoT, 3D Printing, Robotics and CSMI goods. Non-machine-based technologies include Cloud Computing and Big Data Analytics. However, the extreme detail of the ICT survey from ISTAT allows us to extend this complementarity analysis to include three technologies that were excluded from Balsmeier and Woerter (2019)'s taxonomy: IT security, Apps and Augmented Reality. Following the literature on the characteristics of the different technologies, we consider IT security and Apps within the non-machine digital technologies. The descriptive statistics show that these two technologies are more widespread and they only operate on software. Conversely, Augmented Reality is categorized as a machine-based digital technology, because it integrates software and hardware components through its devices.Given that these two types of digital technologies influence different aspects of production, we propose the following third hypothesis:

Hypothesis 3: *Firms that exploit complementarities between machine- and non-machine-based technologies are more resilient to shocks compared to firms that adopted only one type of technology.*

3 Data and methodology

3.1 Data and descriptive statistics

This paper draws on the detailed data on technology adoption of the survey "*Rilevazione sulle tecnologie dell'informazione e della comunicazione nelle imprese*" (from now on, ICT survey) conducted by Istat in 2018 and referring to the adoption in 2016-2017 of a representative sample of active Italian firms with at least 10 employees[1]. The ICT survey of 2018 covers 22,079 firms. The key question concerning investments over the 2016–2017 period was the following: 'In

[1]The ICT survey collects information on ICT usage from a representative sample of small and medium-size Italian firms (with at least 10 employees) and all the large Italian companies (with at least 250 employees), covering both industry and services sectors (Manufacturing; Electricity, gas and steam, water supply, sewerage and waste management; Construction; Wholesale and retail trade repair of motor vehicles and motorcycles; Transportation and storage; Accommodation and food service activities; Information and communication; Real estate activities; Professional, scientific and technical activities; Administrative and support activities; Repair of computers and communication equipment). For this specific analysis, companies operating in the construction sector have been excluded.

the period 2016–2017 did the firm invest in new technologies?'. The respondent could choose among the following technologies: IoT, 3D printing, robotics, cloud computing, big data analytics, augmented reality, IT security, e-commerce, apps and CSMI goods. We use this information to trace the adoption of new digital technologies and of technology bundles. E-commerce is not traditionally classified as a new digital technology in the literature. However, given the specific context of our empirical analysis — the COVID-19 crisis — it plays a relevant role. Therefore, we incorporate it into the descriptive statistics and include it as a control variable in the regression analyses.

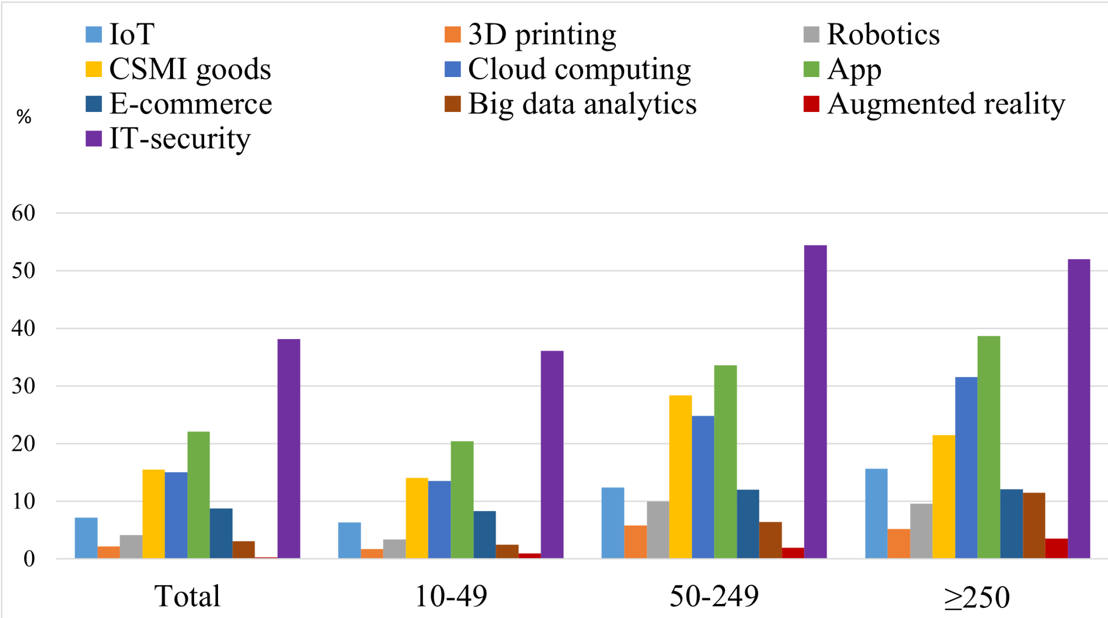
The data from the ICT survey 2018 are merged with multiple longitudinal data sources from Istat, including: i) the Linked Employer-Employee Asia-Employment Register, providing information on the characteristics of firms' workforce, such as age class, education level and type of employment contract; ii) the Linked Employer-Employee "*Registro statistico tematico Annuale su retribuzioni, ore e Costo del Lavoro Individuale*" (RACLI) Register, providing information on hours worked, tenure and professional status of employees; iii) the FRAME-SBS Register, providing information on economic activities (e.g. import/export activity; business group membership) and performance (e.g. value added; turnover) of firms; iv) ASIA-Active firms Register, providing structural firm-level information (e.g. geographical location of companies' headquarters; industry group according to NACE rev.2.2, firm's age). The empirical design requires us to exclude firms that did not survive until 2020, reducing the empirical sample to 20,620 firms observed from 2014 to 2020. In 2018, we observe information on ICT investments for 20,526 firms.[2] As shown in Table A.1 in the Appendix, firms that adopted new digital technologies in 2016–2017 tend to be larger, more productive, and demonstrate stronger economic performance compared to non-adopters. These firms have a workforce structure that relies less on fixed-term and part-time employees while having a higher proportion of highly educated work-

[2]We have no answers regarding the key question about the digital investments in 2016-2017 for 94 firms.

ers and managers. Additionally, adopters of new digital technologies are more likely to be part of a corporate group and to engage in export activities than non-adopters.

Figure 1 shows the total adoption rate of each technology with respect to the total sample size and the distribution of adopters by size classes (with respect to the total of each class). IT security is by far the most widespread digital technology, alone or in combination with other technologies. It is followed by the adoption of apps accessible via the Internet (including management applications), cloud computing and CSMI goods. More complex digital technologies, in particular those belonging to Industry 4.0 enabling technologies, are less diffused, with augmented reality and 3D printing being the two technologies adopted the least. This pattern remains largely consistent across all firm size categories, with IT security being the most widely adopted technology among Italian firms of all sizes. As expected, a significant portion of the other technologies (IoT, cloud computing, apps, and augmented reality) are more widely adopted by larger firms. Notably, the adoption rates of cloud computing and CSMI goods are closely aligned within small and medium-sized firms, which may suggest a potential complementarity between these technologies. On the other hand, large firms have adopted cloud computing more intensively than CSMI goods, highlighting how access to the cloud is a crucial prerequisite for effectively integrating other technologies.

Figure 1: Adoption rate by size class



Notes. The percentages of adoption refer to the total size of the sample for the "Total" group. For the other three groups, the percentages of adoption refer to the total size of each group. In each technology, we consider both the firms that have adopted only that technology and the firms that have adopted that technology together with other ones. Observations weighted using the ICT survey 2018 sampling weights.

Expanding on the characterization of the adoption of new digital technologies in Italy, Figure 2 highlights the correlations between the adoption of various technologies, providing a clear view of the synergies that exist between them. For example, we observe that the adoption of CSMI goods is often paired with IoT or Robotics, while e-commerce is frequently combined with investments in apps, including management applications. The adoption of Cloud Computing, with its enhanced storage and processing capabilities, is strongly correlated with both IoT (which generates vast amounts of data) and Big Data analytics. Importantly, our data suggest significant complementarities between machine-based and non-machine-based technologies, particularly in the combined adoption of IoT with cloud computing, apps, and big data, as well as CSMI goods with apps and big data.

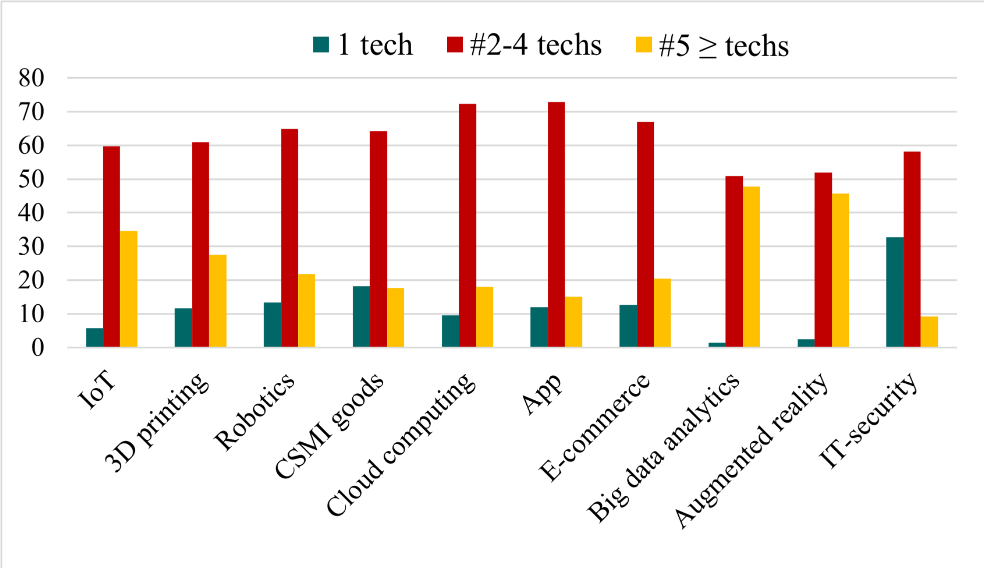
Figure 2: Correlation between technologies adoption

	IoT	3D printing	Robotics	CSMI goods	Cloud computing	App	E-commerce	Big data analytics	Augmented reality
IoT	1.00								
3D printing	0.18	1.00							
Robotics	0.21	0.27	1.00						
CSMI goods	0.32	0.18	0.35	1.00					
Cloud computing	0.25	0.12	0.11	0.19	1.00				
App	0.26	0.11	0.10	0.20	0.44	1.00			
E-commerce	0.13	0.07	0.05	0.08	0.21	0.31	1.00		
Big data analytics	0.28	0.13	0.15	0.19	0.30	0.26	0.18	1.00	
Augmented reality	0.18	0.17	0.12	0.13	0.15	0.15	0.11	0.22	1.00

Going deeper into the analysis, Figure 3 shows the percentage of firms that adopted the technologies alone or in bundles, with reference to the total number of firms adopting each technology. IT security stands out as the technology most frequently adopted alone, however the prevailing trend for all technologies is the adoption of bundles from two to four technologies together. Interestingly, IoT, Big Data Analytics and Augmented Reality exhibit the highest percentages of adoption in large bundles (i.e. together with at least four other technologies), compared to the other technologies.

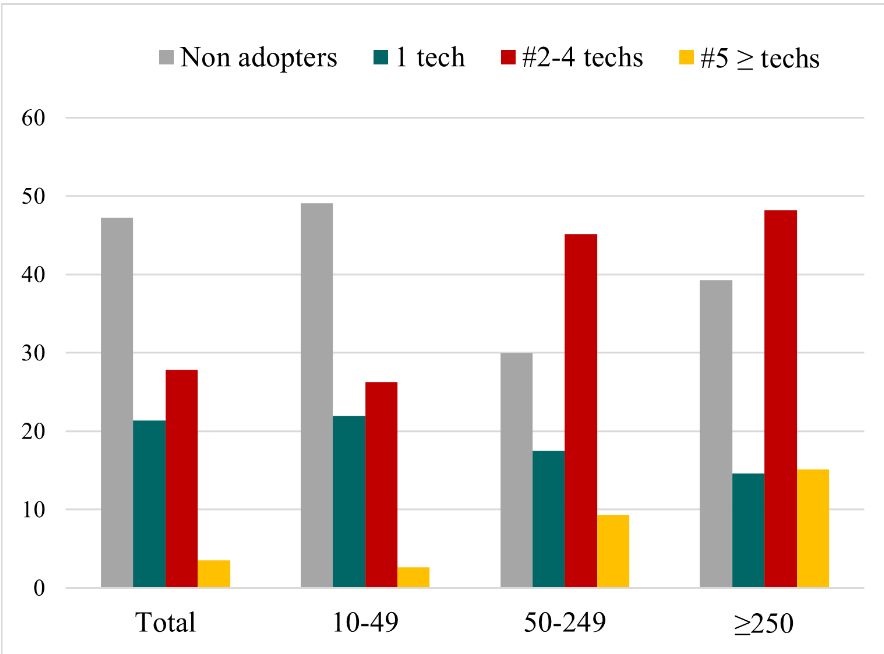
If we combine the information on the number of technologies adopted in bundles and the firms' size categories, we obtain Figure 4. The share of firms adopting only one technology decreases as the size category increases, while the share of firms adopting five or more technologies together shows the opposite trend, with large firms having the highest adoption rate. As expected, the adoption share of bundles comprising two to four technologies increases with size classes, with the majority of firms of both medium and large size adopting such bundles. Medium-sized firms have the lowest percentage of non-adopters (30%), while small and large firms consist of almost 50% and 40% of non-adopters, respectively. Therefore, non-adopters are polarized between small and large firms.

Figure 3: Percentage of technologies adopted in bundles



Notes. The figure shows the percentage of firms (on the vertical axes) adopting only one digital technologies or bundle of technologies. The percentages are calculated on the total number of firms adopting each technology. Observations weighted using the ICT survey 2018 sampling weights.

Figure 4: Percentage of technologies adopted by size class and number of technologies



Notes. The figure shows the percentage of firms (on the vertical axes) that are non adopters, single adopters or bundle adopters withing each size class. Observations weighted using the ICT survey 2018 sampling weights.

3.2 Empirical strategy

To estimate the impact of digital technology adoption on firm resilience to the COVID-19 crisis, we estimate a Difference-in-Differences preceded by 1-to-1 nearest-neighbour Propensity Score Matching (PSM) without replacement (Rosenbaum and Rubin, 1983; 1985; Engel et al., 2019; Czarnitzki et al., 2011). Since the panel is strongly unbalanced, we apply a panel PSM and match treated and control firms for all the pre-treatment years (from 2014 to 2019) of the control variables. [3] As control variables for the PSM we include the NUTS 2 Italian regions, the NACE 1 sector, age classes, size, labour productivity and turnover. The last three variables are transformed using the Hyperbolic Inverse Sine Transformation (HIST), so that we can retain null values and, for the labour productivity, negative values for value added. In general, a well-functioning firm should not report negative values for value added, as this would suggest that costs exceed production value. However, this can occur, and even be relatively common, during crisis periods such as the COVID-19 pandemic. Indeed, our data show that several firms reported positive value-added in previous periods but experienced negative values in 2020. To answer our first research question, we consider as treated all the firms that adopted only one digital technology (IT security, apps, CSMI goods, cloud computing, big data analytics, IoT, robotics, 3D printing and augmented reality) while the control group includes only the firms that did not adopt any digital technology. We then run the PSM on the sample composed of these two groups. After identifying an appropriate control group, we apply a Difference-in-

[3] In order to match on the correct pre-treatment period, we divide the panel in four samples depending on the year of incorporation of the firms. Therefore, we have a first part of the sample with firms incorporated in 2014 or before, a second one with firms incorporated in 2015, the third one with firms incorporated in 2016 and the last one with firms incorporated in 2017. We then perform the panel PSM on each subsample, considering as pre-treatment period for the first subsample the period from 2014 to 2019, for the second subsample the period from 2015 to 2019 and so on. Because of the sample numerosity, we had to remove the firms that were born in 2017 (which accounted for less than 1% of the total sample). It is also noteworthy that, to focus just on manufacturing and services, we exclude from our empirical sample active firms in constructions, which is particularly distinct from the others in terms of production processes, business organization, and output.

Differences methodology and estimate the following linear regression:

$$Y_{i,t} = \alpha + \beta_1 T_i + \beta_2 year2020 + \beta_3 T_i * year2020 + \gamma X_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t}$$

where T_i is the key explanatory variable taking value 1 if the firm belongs to the treatment group, which for the first and second hypothesis includes firms that have adopted only one technology, whatever that might be, and 0 otherwise. The year 2020 is a time indicator for the post-treatment period while the interaction term $\beta_3 T_i * year2020$ identifies the Diff-in-Diff effect of digital investments over the period 2016–2017 on firms' resilience to COVID shock in 2020. $Y_{i,t}$ indicates alternatively the (HIST) turnover, the (HIST) employment and the (HIST) productivity[4]. $X_{i,t}$ represents the set of control variables, including information on workforce age (share of lower-than 35 years-old workers), tenure (share of larger-than 10 years tenured in that job), professional qualification (share of managers and blue collars), work time (share of part-timers) and contract (share of temporary workers); whether the firm is an exporting company, if it is government owned or whether it is or not a member of a corporate group (Italian, or domestic/foreign multinational). The firm's human capital is known to influence its absorptive capacity, which in turn can positively affect its resilience to shocks, making the firm better able to adapt to unforeseen changes. Firm ownership, along with presence in foreign markets is usually linked with different corporate and management strategies that can influence organization resilience, and are therefore relevant aspects to account for in the estimations.

Our specification also includes as controls the age class of firms, the one-year lag of the size variable and one-year lag of gross operating margins (HIST), and the use of e-commerce. Industry controls are included as 2-digit NACE rev.2.2 dummies while geographical location is accounted for using NUTS 2 level, Italian regions. The regression includes year fixed effects

[4]Productivity is here measured using the standard definition of value added over employees. A detailed description of all the variables is in the Appendix.

and firm fixed effects.

We include the pre-treatment values of the three outcome variables among the PSM pre-treatment covariates to align with recent technical literature (Abadie and Imbens, 2011; Roth et al., 2023) showing how the inclusion of pre-treatment outcome values in the matching strategy significantly decreases the overall bias of the estimates when the outcome is highly serially correlated (as in the case of labor productivity, size and turnover) (Ryan, 2018). The validity of the Difference-in-Differences analysis rests on satisfying the Common Trend Assumption (CTA). Therefore, for all the empirical samples considered and for the three dependent variables under investigation (turnover, employment and productivity), we conduct a placebo test. For the placebo test, we set the post-treatment period to start in 2016. The results from both the graphical analysis and the placebo test indicate that the CTA assumption holds true, confirming the validity of our identification strategy. The methodology for the placebo test is detailed in the Robustness Section and in Appendix C.

4 Results

To test our first hypothesis, we compare firms that adopted only one technology against those that did not implement any technology at all in 2016-2017[5]. The results of the DiD estimations are reported in Table 1. As expected, our estimations confirm that the COVID-19 pandemic led to a substantial disruption of turnover, employment, and productivity across all firms. Notably, the relatively smaller coefficient associated with employment reflects firms' limited ability to dismiss workers as the pandemic unfolded. This was driven not only by government measures—such as the so-called "Blocco dei licenziamenti"—aimed at preventing mass layoffs, but also by a common firm-level strategy of adjusting the intensive margin of labor input to

[5]We consider as treated the firms that adopted only one technology among IoT, Robotics, 3D printing, CSMI goods, Apps, Cloud Computing, Big Data Analytics, IT security and Augmented Reality.

cope with the decline in economic activity. However, concerning the coefficient of interest, the prior adoption of a single technology did not determine any improvements in the resilience of firms compared to non-adopters, neither in terms of turnover, employment nor productivity. Therefore, our first hypothesis is not supported, as it shows that minimal levels of digitalization were insufficient to make firms resilient to the COVID-19 crisis.

Table 1: Diff-in-Diff fixed effects estimate: Single technology adoption vs. Non-adopters

	Turnover	Employment	Productivity
year2020	-0.227***	-0.0466***	-0.559***
	(0.0277)	(0.00764)	(0.0738)
Single Tech Adoption * year2020	0.0270	0.00831	-0.129
	(0.0244)	(0.00813)	(0.0929)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.79***	1.128***	7.478***
	(0.437)	(0.202)	(1.028)
N of Obs	34627	34628	34627
N of firms	6964	6964	6964
R^2	0.038	0.459	0.144

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

However, a high proportion of adopters in our estimation sample (17.5%) invested uniquely in IT security measures, and this may not be surprising when we consider the fast increasing emphasis on data security and data protection concerns. It is therefore important to verify the influence of these adopters on our results. Accordingly, we conducted a robustness analysis to validate our first hypothesis. This analysis excluded firms that adopted only IT security from the treated group. The treated group was redefined to include firms adopting only IoT, 3D printing, Robotics, CSMI goods, Cloud computing, Apps, Big Data Analytics, and Augmented Reality[6]. The results of this robustness check (Table 2) are consistent with our original findings

[6]We employ a 1-nearest neighbor PSM approach to identify the most appropriate control group given this new

(Table 1), confirming that prior single adoption of digital technologies did not improve firm resilience during the COVID-19 pandemic, and that this conclusion is not driven by firms that only adopted IT security.

Table 2: Diff-in-Diff fixed effects estimate: Single technology adoption (excluding IT security) vs. Non-adopters

	Turnover	Employment	Productivity
year2020	-0.244***	-0.0517***	-0.562***
	(0.0398)	(0.0119)	(0.104)
Single Tech Adoption * year2020	0.00799	0.0171	-0.210
	(0.0391)	(0.0126)	(0.145)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.25***	1.532***	11.15***
	(2.731)	(0.215)	(0.823)
N of Obs	14590	14590	14590
N of firms	2938	2938	2938
R^2	0.141	0.491	0.054

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

For our second hypothesis, we then proceeded to estimate the Difference-in-Differences by considering as treated those firms that adopted only one technology, and as the control group those firms that adopted two or more technologies in 2016-2017. Given the strong imbalance in the panel data, we employed again a 1-to-1 nearest neighbor PSM method to account for selection into treatment based on observables, resulting in a more reliable sample of comparable firms. The results presented in Table 3 indicate that firms adopting only one technology were significantly more impacted by the crisis and, consequently, less resilient compared to those that adopted two or more digital technologies simultaneously in 2016-2017. This finding holds for all the three outcome variables we consider, with a stronger statistical significance for turnover

definition of the treatment group.

and productivity. The second hypothesis is therefore confirmed, with the results highlighting how the combined use of multiple technologies (i.e. the breadth of adoption), enabled firms to increase their resilience, successfully mitigating the negative effects of the crisis on all the performance outcomes under investigation.

Table 3: Diff-in-Diff fixed effects estimate: Single technology adoption vs. At least two technologies adopted

	Turnover	Employment	Productivity
year2020	-0.131***	-0.0317***	-0.394***
	(0.0208)	(0.00826)	(0.0799)
Single Tech Adoption * year2020	-0.0545***	-0.0151*	-0.298***
	(0.0206)	(0.00785)	(0.0926)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.74***	1.273***	10.49***
	(2.529)	(0.181)	(2.374)
N of Obs	34653	34653	34653
N of firms	6970	6970	6970
R^2	0.159	0.467	0.036

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We deepen the analysis on technological complementarities, extending the definition of machine-based and non-machine-based digital technologies provided by Balsmeier and Woerter (2019) to include all the digital technologies. More specifically, we compare firms that adopted (at least) one machine-based technology joint with (at least) one non-machine-based technology with firms adopting either only (at least) one non-machine-based digital technologies or (at least) one machine-based digital technologies. Extending Balsmeier and Woerter (2019) definitions, we consider as machine-based technologies IoT, 3D Printing, Robotics, CSMI Goods and Augmented Reality. Conversely, non-machine-based technologies include Cloud Computing, Big Data Analytics, Apps and IT security. The results (Table 4) show that the exploitation of technological complementarities increases firm resilience according to all the three dimensions under analysis: turnover, employment and productivity. Therefore, complementarities significantly contribute to reduce firms' losses during the crisis compared to firms engaged in a unique type of technologies, either machine- or non-machine-based digital technologies.

Table 4: Diff-in-Diff fixed effects estimate: Machine and non-machine adopters vs. only non-machine or only machine digital technologies adopters

	Turnover	Employment	Productivity
year 2020	-0.0994***	-0.0104	-0.489***
	(0.0192)	(0.00758)	(0.0674)
Treatment * year 2020	0.0413***	0.0192***	0.176**
	(0.0147)	(0.00618)	(0.0684)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	14.12***	1.839***	7.744***
	(0.365)	(0.178)	(1.063)
N of Obs	43665	43665	43665
N of firms	8774	8774	8774
R^2	0.172	0.515	0.042

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5 Heterogeneity Analysis

5.1 Heterogeneity by technology

To gain a deeper understanding of the dynamics at play and the complementary effects of adopting technology bundles, we now turn our attention to the specific impact of Robotics, IoT, and Big Data. These three technologies represent a diverse array of applications, ranging from physical technologies, such as Robotics, to computational (intangible) ones such as Big Data Analytics. In their comparative study of new digital technologies, Martinelli et al. (2021) analyse technological similarity both by source and by use of technological knowledge as captured by the cosine similarity of the knowledge base cited in patents and the cosine similarity of forward citations to patents respectively. In terms of use of technological know-how, Robotics, IoT and Big data analytics are more different from one another than from the other technologies, and can be expected to yield distinctive effects on firm performance. While we include in the Appendix B detailed analyses for each technology, here we focus on these three technologies to provide illustrative evidence on the role of technological heterogeneity.

Focusing first on Robotics (Table 5), we analyse the resilience to COVID-19 pandemics of firms that adopted Robotics either alone or in combination with other technologies in 2016-2017, comparing them to firms that did not adopt any new digital technology. As in previous analyses, the Difference-in-Differences estimation is preceded by PSM to obtain a comparable control group. The results are displayed in Table 5. As expected, the adoption of Robotics significantly enhanced firm resilience, mitigating the adverse effects of the crisis and contributing to greater stability in turnover, employment, and productivity during the shock. Given that Robotics is primarily centered on production processes, which were notably disrupted by necessary measures to curb the spread of the virus, such as social distancing and the closure of production facilities, its impact on resilience is particularly relevant.

Continuing our analysis of individual technologies, we now turn our attention to IoT (Table 5). Similarly to Robotics, the prior integration of IoT into a firm's processes — whether implemented alone or in conjunction with other technologies — enhances resilience in terms of turnover, employment and productivity.

Next, we conducted the same analysis for firms that adopted Big Data Analytics in 2016-2017 (Table 5). The results mirror those observed with Robotics and IoT, showing that the adoption of Big Data Analytics prior to the crisis reduced turnover losses. However, differently from the previous cases, the adoption of Big Data Analytics did not alleviate the drop neither on productivity nor on employment. When examining the impact of Robotics, IoT, and Big Data on turnover, it appears that IoT had the most significant effect, resulting in a 13.2% reduction in turnover losses during the COVID-19 crisis. The adoption of IoT has also the most substantial impact on the net effect of adoption on turnover. Adopters of IoT experienced a turnover loss of 5.9%, compared to a 11.7% drop for firms that adopted Big Data Analytics and a 8.8% drop for those that adopted Robotics. However, if we focus on the net effect of the three technologies on productivity and employment, we see that Robotics has a strong statistically significant impact on both, while this is true for IoT only in terms of employment. In particular, firms that had previously adopted Robotics experience a total loss of productivity of only 1% despite the crisis. [7].

5.2 Heterogeneity by sector

To better understand the interconnection between technology adoption and resilience, we conduct additional analyses to identify effects that might be specific to macro-sectors, i.e. manufacturing vis-à-vis service industries[8]. Following the same order and rationale used for the results presented in the previous section, in Table 6 we illustrate the findings of the heterogeneity analysis for manufacturing and service sectors considering as treatment group the firms that adopted only one technology compared to the firms that did not adopt any technology. In Table 6 we present the results of two Difference-in-Differences conducted on the split samples

[7] The net effects of technology adoption on turnover and productivity are calculated as $\beta_2 + \beta_3$, with reference to our linear regression model.

[8] Following the NACE code and Istat definitions, we define the firms belonging to the 1-digit NACE code C as Manufacturing. The firms belonging to the 1-digit NACE codes from G to T are defined as Services. They include Wholesale and Retail, Transport and Storage, Accommodation and Catering services, ICT services, Financial and Insurance Activities, Real Estate activities, Professional, Scientific and Technical activities, Administrative and Support Service activities, Artistic and Entertainment activities, Domestic staff and goods and services for households. The sectors that are not defined neither as Manufacturing nor as Services are Agriculture, forestry and fisheries, Mining, Supply of electricity, gas, steam and air conditioning, Water supply, sewerage, waste treatment and sanitation activities.

Table 5: Differences-in-Differences by technology

	Robotics			IoT			Big Data Analytics		
	Turnover	Employment	Productivity	Turnover	Employment	Productivity	Turnover	Employment	Productivity
year2020	-0.153***	0.00896	-0.344***	-0.191***	-0.0369***	-0.653***	-0.198***	-0.00443	-0.331***
	(0.0392)	(0.0116)	(0.109)	(0.0339)	(0.0111)	(0.0837)	(0.0526)	(0.0128)	(0.111)
Technology Adoption *	0.0651***	0.0309***	0.334***	0.132***	0.0440***	0.193*	0.0812**	0.0218	-0.118
year2020	(0.0204)	(0.00883)	(0.0945)	(0.0270)	(0.0110)	(0.100)	(0.0341)	(0.0136)	(0.153)
Workforce characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	14.45***	2.340***	12.46***	14.66***	2.031***	8.008***	13.69***	2.233***	8.258***
	(0.731)	(0.298)	(1.592)	(0.469)	(0.223)	(1.043)	(0.771)	(0.289)	(1.651)
N of Obs	11085	11085	11085	22466	22466	22466	13606	13606	13606
N of firms	2228	2228	2228	4516	4516	4516	2738	2738	2738
R^2	0.249	0.546	0.114	0.164	0.463	0.054	0.171	0.525	0.036

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

of manufacturing-only industries and service-only industries. The findings reveal that single technological adoption has a statistically significant effect on resilience in the manufacturing sector for turnover and employment, while it does not have any effect neither on manufacturing productivity nor on the service sector. This indicates that the effect of adopting a single technology on resilience against the COVID-19 crisis — measured in terms of turnover, employment, or productivity — is not even across different sectors.

Table 6: Split sample by macro-sector: Single technology adoption vs. Non-adopters

	Sector Group : Manufacturing			Sector Group: Service		
	Turnover	Employment	Productivity	Turnover	Employment	Productivity
year2020	-0.128***	-0.0227*	-0.222**	-0.292***	-0.0616***	-0.726***
	(0.0292)	(0.0118)	(0.109)	(0.0366)	(0.00990)	(0.0965)
Single Tech Adoption * year2020	0.0571**	0.0293***	0.00975	0.0161	0.000186	-0.189
	(0.0285)	(0.0113)	(0.127)	(0.0316)	(0.0108)	(0.124)
Workforce characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.10***	0.506***	10.18***	13.21***	1.423***	8.862***
	(0.775)	(0.178)	(1.593)	(0.403)	(0.149)	(0.907)
N of Obs	7945	7945	7945	24080	24080	24080
N of firms	1631	1631	1631	4889	4889	4889
R^2	0.198	0.524	0.035	0.160	0.527	0.040

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Turning to the sector heterogeneity analysis as part of our robustness check on the first hypothesis, we find results consistent to the previous evidence. Indeed, notwithstanding the exclusion of the firms that adopted only IT security, the manufacturing sector demonstrated an increase in resilience, measured by turnover and employment attributable to the prior adoption of a single digital technology (Table 7), whereas in services, single-technology did not perform differently than their non-adopting counterparts. These results demonstrates the robustness of our findings.

Table 7: Split sample by macro-sector: Single technology adoption (exluding IT security) vs. Non-adopters

	Sector Group : Manufacturing			Sector Group: Service		
	Turnover	Employment	Productivity	Turnover	Employment	Productivity
year2020	-0.141**	-0.0127	-0.471***	-0.311***	-0.0734***	-0.717***
	(0.0650)	(0.0119)	(0.136)	(0.0537)	(0.0160)	(0.139)
Single Tech Adoption * year2020	0.101**	0.0444***	0.0331	-0.0223	0.00238	-0.310
	(0.0474)	(0.0162)	(0.211)	(0.0530)	(0.0168)	(0.197)
Workforce characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	11.21***	1.190***	4.615	13.59***	1.856***	9.214***
	(1.924)	(0.397)	(3.880)	(0.662)	(0.289)	(1.841)
N of Obs	3587	3587	3587	9901	9901	9901
N of firms	736	736	736	2012	2012	2012
R^2	0.193	0.560	0.049	0.133	0.471	0.055

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In Table 8, we present the results concerning our second hypothesis - i.e. comparing firms that adopted only one technology with those that adopted two or more technologies - for the split samples of manufacturing and services industries, respectively. The Table clearly shows that the results obtained from the prior combined adoption of two or more technologies with respect to a single-technology adoption are driven, perhaps surprisingly, by the service sector. We do not register any statistically significant effect on the manufacturing sample as far as our outcome variables are concerned. Conversely, service firms that had adopted only one technology in 2016-2017 experienced an additional 9.3% decline in turnover compared to those that had adopted at least two technologies.

Table 8: Split sample by macro-sector: Single technology adoption vs. adopters of at least 2 technologies

	Sector Group : Manufacturing			Sector Group: Service		
	Turnover	Employment	Productivity	Turnover	Employment	Productivity
year2020	-0.0726**	-0.00954	-0.101	-0.155***	-0.0381***	-0.549***
	(0.0311)	(0.0120)	(0.114)	(0.0232)	(0.0107)	(0.106)
Single Tech Adoption * year2020	0.00578	0.0115	-0.139	-0.0926***	-0.0285***	-0.354***
	(0.0247)	(0.0101)	(0.122)	(0.0247)	(0.0103)	(0.124)
Workforce characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.63***	1.244***	10.08***	13.58***	1.229***	8.872***
	(0.987)	(0.247)	(2.263)	(0.375)	(0.192)	(1.368)
N of Obs	7982	7982	7982	24087	24087	24087
N of firms	1645	1645	1645	4888	4888	4888
R^2	0.224	0.580	0.049	0.149	0.435	0.038

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This highlights the substantial positive effect of the breadth of adoption on the resilience of the service sector, an especially interesting result if we consider that service firms were among the worst affected by the crisis.

When examining sectoral heterogeneity for Robotics (Table 9), and comparing firms that adopted at least robotics to those that adopted no new technologies, we find that the effect of prior robotics adoption on resilience is statistically significant primarily within the manufacturing sector. In contrast, the service sector seems to experience only a marginally significant benefit from prior robotics adoption. Given that the overall results in Table 5 show a positive and statistically significant effect of Robotics adoption on productivity during the COVID-19 period, we can conclude that this positive effect is largely driven by the manufacturing sector.

Table 9: Split sample by macro-sector: Robotics

	Sector Group : Manufacturing			Sector Group: Service		
	Turnover	Employment	Productivity	Turnover	Employment	Productivity
year2020	-0.125***	-0.00445	-0.315***	-0.186*	0.0106	-0.455**
	(0.0237)	(0.0104)	(0.108)	(0.0975)	(0.0242)	(0.229)
Robotics * year2020	0.0487**	0.0213***	0.319***	0.119*	0.0392	0.421*
	(0.0203)	(0.00821)	(0.109)	(0.0670)	(0.0283)	(0.252)
Workforce characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.18***	1.811***	14.58***	13.77***	2.131***	9.128***
	(1.645)	(0.306)	(0.484)	(0.928)	(0.292)	(2.512)
N of Obs	7836	7836	7836	2976	2976	2976
N of firms	1588	1588	1588	626	626	626
R^2	0.060	0.545	0.340	0.216	0.528	0.148

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

When exploring the heterogeneity for Big Data Analytics (Table 10), we substantially notice the opposite dynamics compared to Robotics: in this case only the service sector responds positively to prior adoption of the technology, enahncing firms' resilience in terms of turnover and employment, while the manufacturing sector remains basically unchanged.

Finally, in Table 11, firms adopting IoT in both the manufacturing and the service sector experience an increase in their resilience.

Table 10: Split sample by macro-sector: Big Data Analytics

	Sector Group : Manufacturing			Sector Group: Service		
	Turnover	Employment	Productivity	Turnover	Employment	Productivity
year2020	-0.149***	0.00790	-0.0585	-0.224***	-0.0150	-0.498***
	(0.0365)	(0.0153)	(0.139)	(0.0747)	(0.0182)	(0.149)
Big Data Analytics * year2020	-0.0352	-0.0286*	-0.429*	0.141***	0.0464**	0.0747
	(0.0347)	(0.0148)	(0.250)	(0.0467)	(0.0187)	(0.193)
Workforce characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.31***	2.615***	14.14***	10.91***	1.868***	6.576***
	(0.882)	(0.438)	(2.362)	(0.770)	(0.256)	(1.669)
N of Obs	3563	3563	3563	8954	8954	8954
N of firms	728	728	728	1821	1821	1821
R^2	0.466	0.583	0.069	0.148	0.505	0.039

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: Split sample by macro-sector: IoT

	Sector Group : Manufacturing			Sector Group: Service		
	Turnover	Employment	Productivity	Turnover	Employment	Productivity
year2020	-0.148***	-0.0211	-0.375***	-0.187***	-0.0621***	-0.866***
	(0.0284)	(0.0139)	(0.111)	(0.0417)	(0.0162)	(0.119)
IoT * year2020	0.0579**	0.0246**	0.129	0.158***	0.0516***	0.210
	(0.0232)	(0.0106)	(0.152)	(0.0383)	(0.0173)	(0.150)
Workforce characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	15.15***	2.006***	13.58***	13.50***	1.815***	7.785***
	(0.776)	(0.500)	(1.488)	(0.587)	(0.311)	(1.794)
N of Obs	7199	7199	7199	13148	13148	13148
N of firms	1470	1470	1470	2677	2677	2677
R^2	0.341	0.519	0.055	0.121	0.437	0.057

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6 Robustness checks

6.1 Placebo tests

The validity of the Difference-in-Differences (DiD) analysis depends on the Common Trend Assumption (CTA). To validate this assumption, we conduct a placebo test by artificially shifting the post-treatment period from 2020 to 2016 (Miller et al., 2021). If our identification strategy is correct and we successfully isolate the impact of previously adopted digital technologies on resilience to the COVID-19 crisis, we should not observe any statistically significant effects in the treatment group for the 2016 "post-treatment" period. This placebo test effectively checks for the presence of different trends in the outcome variables between the treatment and control groups before the event under analysis. We apply the placebo test to all three outcome variables — turnover, employment, and productivity — across the three samples designed to address each of our three main hypotheses. The results of the placebo test (Appendix C) show no significant effects, confirming that the CTA assumption holds and validating the accuracy of our identification strategy.

6.2 Governmental closure of economic activities

The Italian government implemented various measures to limit the spread of COVID-19, with the most stringent being the enforcement of social distancing and the mandated closure of specific business sectors. In Italy, these mandated closure were dictated by a set of laws between March and May 2020. The closures primarily affected establishments dedicated to physical activities, such as gyms and swimming pools; venues for leisure activities (such as theaters, museums, spas); retail businesses; transportation and equipment rentals; and touristic related activities (tour operators, hotels, hostels, touristic guides). These activities have been closed since the beginning of the pandemic. Another set of activities was instead closed from March 2020 to early May 2020, but they were allowed to continue their production with the last law enacted in May 2020. These other set of activities include mining activities; fabrication of textiles, clothing and footwear; manufacture of building materials (such as lime, bricks, ceramics); metal production; manufacture of metal objects and electrical appliances; production of transportation means (like cars and scooters); production of furniture; and wholesale businesses[9]. Given that these sectors were completely shut down by law, the adoption of digital technologies may have had only a very limited effect on their turnover, employment, or productivity during the pandemic. To account for potential bias resulting from forced temporary business closures, a dummy variable was included in the analysis. We conducted this robustness test controlling

[9]For a complete and detailed list of sectors closed by the Government during the COVID-19 pandemic: Closed Activities during COVID-19 - link ISTAT

for either all the sectors that have been closed with any law from March to May or only the sectors that have been closed continuously from March on, excluding those that were re-opened in May 2020. The inclusion of this additional control confirmed the original findings, ensuring the robustness of the results (results in Appendix D).

6.3 Technology-specific complementarities

As an additional robustness check for the second hypothesis, we conducted separate Difference-in-Differences analyses for each technology, to detect a potential technology-specific complementarity effect. This analysis addresses the varying impact of prior investment in a specific technology whether adopted alone, as part of a bundle of two to four technologies, or within a bundle of at least five technologies, compared to firms that did not adopt any technology. This additional analysis reveals that most of the technologies had positive and statistically significant effects on resilience only when used in bundles. More specifically (results in Appendix E), IoT, Apps and Cloud Computing increased resilience only for firms that adopted them alongside at least one other digital technology. Robotics is the only technology that significantly increases resilience in terms of productivity even if adopted alone compared to firms that did not adopt any technology at all. However, its impact is even stronger when adopted in bundles, positively affecting resilience in terms of turnover and employment as well. Big Data Analytics significantly increased turnover resilience when adopted in bundles with at least another technology while its effect on employment turns out statistically significant only if adopted within at least other four technologies.

6.4 The role of adopting any digital technology

To ensure the robustness of our results from the technological heterogeneity analysis (Section 5.1), we aim to test a broader version of the underlying hypothesis, by examining whether the prior adoption of at least one (rather than a specific one) digital technology enhances resilience. Indeed, in Section 5.1 the aim was to test the effectiveness of specific relevant technologies, either alone or in combination with others. However, given the higher proportion of firms that adopted at least one digital technology between 2016 and 2017 across all technologies (IoT, 3D printing, Robotics, CSMI goods, Cloud Computing, Apps, Big Data Analytics, Augmented Reality and IT security) with respect to non-adopters, it is not feasible to generate an appropriate counterfactual for the full sample using Propensity Score Matching (PSM). Nonetheless the application of PSM remains essential for conducting a Difference-in-Differences (DiD) analysis, as we know that adopters tend to outperform the average Italian firm. To tackle this difficulty, we draw a stratified random sample of firms that adopted at least one digital technology. The stratification is designed to obtain a representative subsample of treated firms in terms of 2-digit NACE rev.2 code, region (NUTS 2) and size class. Once obtained the (stratified random) subsample of the treated firms, we employed a 1-nearest neighbor PSM approach to define a proper control group, followed by the Difference-in-Differences analysis. In line with our expectations and with what emerged by the technological heterogeneity analysis, the results (detailed in Appendix F) indicate that firms that had previously adopted at least one digital technology, in 2020 experienced smaller losses in terms of turnover (almost the half in magnitude), no losses in terms employment and about a 40 percentage smaller losses in productivity.

7 Conclusions

In recent years, academic debate has centered on the transformative effects of new digital technologies on the economy, particularly in terms of firm performance. This has sparked renewed interest in the concept of resilience, especially in relation to disruptive exogenous events such as the COVID-19 pandemic. New technologies span a wide array of industries, offering diverse opportunities, functionalities and solutions that can enhance the resilience of firms to crises. Previous contributions focused on regional dynamics, or industry-specific aspects of the COVID-19 crisis, and when they addressed the firm level, they relied on surveys with limited sample sizes and overly broad definitions of digitalization. In this paper we explore how different digital technologies and their complementarities affected firm resilience by applying a Diff-in-Diff analytical framework to a rich and unique set of microdata. The context of this analysis - the Italian economy - is highly suited to our research aims and objectives because Italy was severely affected by the COVID-19 crisis and by the measures implemented to curb the spread of the virus.

Our findings show that the adoption of new digital technologies before the pandemic had substantial effects on firm resilience during the COVID-19 crisis, helping to mitigate its adverse effects (Bai et al., 2021). The results highlight the critical role digital technologies play in maintaining operational stability during crises, enabling firms to adapt to disruptions production and service delivery, and exogenous shifts in demand and the economic landscape more broadly (Williams et al., 2017; Conz and Magnani, 2020; Santoro et al., 2021; Crespo et al., 2023; Lien and Timmermans, 2024). A firm's capacity to sustain production throughout the COVID-19 pandemic was closely linked to its prior investment in digital technologies, which became vital to manage the effects of lockdowns, social distancing measures, and border closures (Pereira et al., 2022; Ladeira et al., 2019).

Interestingly, however, our results indicate that the intensity of digitalization efforts was very important: adopting only one new technology was insufficient to enhance resilience. Conversely, resilience was significantly higher when firms leveraged the potential of multiple technologies and exploited technological complementarities. A multi-technology approach mitigated turnover, employment, and productivity losses caused by the crisis. More specifically, the joint adoption of machine-based and non-machine-based technologies proved very effective since firms that adopted and integrated both types of technologies displayed significantly higher resilience. When examining the impact of specific technologies on resilience, we found that the adoption of Robotics, IoT, and Big Data Analytics — whether individually or in combination with other technologies — successfully mitigated the negative effects of the crisis on productivity. In particular, prior investments in Robotics almost completely counterbalanced productivity losses in 2020, while the effectiveness of Iot stood out in mitigating the decline of turnover. Sectoral analysis further revealed important heterogeneity in these effects. The manufacturing sector experiences enhanced resilience with prior adoption of even a single digital technology. However, the enhanced resilience resulting from adopting bundles of new digital technologies was primarily driven by firms in the service sector; by contrast, no significant effect was observed in the manufacturing sector. At the technology level, instead, Robotics played a key role in increasing resilience within manufacturing sectors and only a marginal impact on the service sector. Conversely, Big Data Analytics significantly enhanced resilience in the service sector but did not influence outcomes in manufacturing.

Qualitative studies could provide deeper insights into the organizational dynamics of digitalization, but this systematic quantitative evidence on the positive effects of digitalization is crucial. It highlights the importance of specific technological heterogeneity and the complementarities necessary to fully capture the benefits of new digital technologies. This insight also points to the distinct opportunities that different technologies provide to adopters, and the advantages brought about by technological synergies. Finally, it offers an interesting perspective on the sectoral heterogeneity of business performances against exogenous shocks, and how digital technologies can mitigate or exacerbate their impacts conditional on the sectoral context of application.

From a policy perspective, our analysis suggests that comprehensive and integrated innovation policies that promote multi-technology adoption should be prioritized over isolated incentive schemes that do not encourage the complementary adoption of multiple technologies. Building on this line of inquiry, future research could explore not only the long-term effects of technology adoption on competitive dynamics, but also qualitatively investigate the governance of digital technological complementarities. This would help to better identify which policy tools are most effective in promoting the digital transformation of the Italian economy.

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8 Appendix

A Data and variable definition

Table A.1: Descriptives calculated over sample firms that either non adopted or adopted at least one ICT in 2016-2017 (20,526 firms). Year 2018.

	No ICT adopters		ICT adopers		95% CI for mean difference	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	T-statistics	p-value
Labour productivity	62,718	109,392	80,756	151,487	-9.67	0.000
Employment	65	235	247	1,671	-9.36	0.000
Turnover	2.E+07	1.E+08	8.E+07	5.E+08	-10.89	0.000
EBITDA	1.E+06	1.E+07	8.E+06	8.E+07	-7.16	0.000
Number of digital techologies adopted	0	0	3	2	-140.00	0.000
Temporary workers (% share)	12	17	10	16	6.8758	0.000
Part-time workers (% share)	22	27	16	22	16.81	0.000
Managers (% share)	1	3	1	3	-14.61	0.000
Blue collars (% share)	58	33	46	33	25.04	0.000
Tenure >10 years (% share)	32	27	37	27	-12.88	0.000
Women (% share)	35	28	35	25	-0.312	0.755
Tertiary education (% share)	11	16	18	19	-25.77	0.000
Workers <35 years old (% share)	13.8	14.1	13	13	3.54	0.000
Government owned company	0.0	0.1	0.0	0.2	-8.742	0.000
Membership to domestic corporate group	0.2	0.4	0.3	0.4	-5.36	0.000
Membership of foreign multinational	0.1	0.2	0.1	0.3	-13.00	0.000
Membership of Italian multinational	0.1	0.2	0.2	0.4	-22.78	0.000
No group membership	0.6	0.5	0.4	0.5	28.35	0.000
Exporter	0.2	0.4	0.4	0.5	-30.00	0.000
Observations	7,507		13,019		20,526	

Source: our calculations on Istat data.

B Technology-specific results

Table B.1: Difference-in-Differences by technology: 3D Printing

	Turnover	Employment	Productivity
year 2020	-0.202***	-0.0298**	-0.390**
	(0.0686)	(0.0136)	(0.156)
3D Printing * year 2020	0.0235	0.0188*	0.0589
	(0.0459)	(0.0114)	(0.167)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.04***	1.323***	12.98***
	(1.438)	(0.297)	(1.963)
N of Obs	6451	6451	6451
N of firms	1294	1294	1294
R^2	0.296	0.613	0.080

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

Table B.2: Difference-in-Differences by technology: CSMI goods

	Turnover	Employment	Productivity
year 2020	-0.188***	-0.0346***	-0.569***
	(0.0224)	(0.00825)	(0.0641)
CSMI goods * year 2020	0.0983***	0.0542***	0.209***
	(0.0211)	(0.00742)	(0.0709)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	13.73***	1.562***	5.972***
	(0.792)	(0.233)	(1.964)
N of Obs	36195	36195	36195
N of firms	7282	7282	7282
R^2	0.147	0.459	0.044

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

Table B.3: Difference-in-Differences by technology: Cloud Computing

	Turnover	Employment	Productivity
year 2020	-0.207***	-0.0565***	-0.589***
	(0.0204)	(0.00766)	(0.0649)
Cloud Computing * year 2020	0.113***	0.0411***	0.197***
	(0.0198)	(0.00801)	(0.0757)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	13.45***	1.803***	7.867***
	(0.463)	(0.203)	(1.250)
N of Obs	45389	45389	45389
N of firms	9140	9140	9140
R^2	0.153	0.461	0.029

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

Table B.4: Difference-in-Differences by technology: App

	Turnover	Employment	Productivity
year 2020	-0.245***	-0.0681***	-0.681***
	(0.0196)	(0.00664)	(0.0594)
App * year 2020	0.0915***	0.0357***	0.178**
	(0.0178)	(0.00757)	(0.0705)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	13.06***	1.624***	6.868***
	(0.449)	(0.219)	(1.596)
N of Obs	58958	58958	58958
N of firms	11866	11866	11866
R^2	0.167	0.440	0.035

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

Table B.5: Difference-in-Differences by technology: Augmented Reality

	Turnover	Employment	Productivity
year 2020	-0.0515	-0.00984	-0.358*
	(0.0701)	(0.0263)	(0.197)
Augmented Reality * year 2020	0.0779	0.0453*	0.163
	(0.0611)	(0.0252)	(0.206)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	14.69***	2.113***	12.07***
	(0.693)	(0.292)	(2.247)
N of Obs	4139	4139	4139
N of firms	832	832	832
R^2	0.135	0.587	0.121

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

C Placebo tests

Table C.1: Placebo test: Single technology adoption vs. Non-adopters

	Turnover	Employment	Productivity
Post-treatment $\geq$ 2016	-0.214***	-0.0442***	-0.609***
	(0.0239)	(0.00715)	(0.0692)
Single Tech Adoption * Post-treatment $\geq$ 2016	0.000941	0.00310	-0.0230
	(0.0159)	(0.00619)	(0.0571)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.80***	1.129***	7.450***
	(0.437)	(0.202)	(1.028)
N of Obs	34627	34627	34627
N of firms	6964	6964	6964
R^2	0.144	0.459	0.038

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

Table C.2: Placebo test: Single technology adoption vs. At least two other technologies

	Turnover	Employment	Productivity
Post-treatment $\geq$ 2016	-0.152***	-0.0376***	-0.545***
	(0.0195)	(0.00784)	(0.0740)
Single Tech Adoption * Post-treatment $\geq$ 2016	-0.0159	-0.00432	-0.0197
	(0.0159)	(0.00608)	(0.0574)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.74***	1.271***	10.46***
	(0.536)	(0.181)	(2.535)
N of Obs	34653	34653	34653
N of firms	6970	6970	6970
R^2	0.159	0.466	0.036

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

Table C.3: Placebo: Machine and non-machine-digital technologies

	Turnover	Employment	Productivity
Post-treatment $\geq$ 2016	-0.0468***	0.00003	-0.351***
	(0.0178)	(0.00772)	(0.0776)
Treatment * Post-treatment $\geq$ 2016	0.0162	0.00154	0.0651
	(0.0170)	(0.00618)	(0.0585)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	14.98***	2.798***	9.278***
	(0.381)	(0.349)	(1.254)
N of Obs	27164	27164	27164
N of firms	5462	5462	5462
R^2	0.245	0.575	0.053

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

D Governmental closure of economic activities

Table D.1: Closed sectors: Single technology adoption vs. Non-adopters

	Turnover	Employment	Productivity
year 2020	-0.190***	-0.0534***	-0.354***
	(0.0305)	(0.00866)	(0.0791)
Single Tech Adoption * year 2020	0.0191	0.00628	-0.166*
	(0.0240)	(0.00812)	(0.0919)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.78***	1.118***	7.451***
	(0.437)	(0.203)	(1.028)
N of Obs	34627	34627	34627
N of firms	6964	6964	6964
R^2	0.150	0.460	0.048

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

Table D.2: Closed sectors: Single technology adoption (excluding IT security) vs. Non-adopters

	Turnover	Employment	Productivity
year 2020	-0.231***	-0.0614***	-0.373***
	(0.0474)	(0.0138)	(0.124)
Single Tech Adoption * year 2020	0.00508	0.0161	-0.221
	(0.0388)	(0.0126)	(0.144)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.27***	1.528***	11.32***
	(0.828)	(0.215)	(2.725)
N of Obs	14590	14590	14590
N of firms	2938	2938	2938
R^2	0.144	0.492	0.063

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

Table D.3: Closed sectors: Single technology adoption (excluding IT security) vs. At least two technologies adopters

	Turnover	Employment	Productivity
year 2020	-0.102***	-0.0390***	-0.205**
	(0.0234)	(0.00938)	(0.0892)
Single Tech Adoption * year 2020	-0.0442**	-0.0131*	-0.262***
	(0.0207)	(0.00788)	(0.0915)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.73***	1.270***	10.43***
	(0.534)	(0.181)	(2.543)
N of Obs	34653	34653	34653
N of firms	6970	6970	6970
R^2	0.167	0.468	0.045

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.

E Technology-specific complementarities

Table E.1: IoT discrete Diff-in-Diff by number of technologies adopted in bundles

	Turnover	Employment	Productivity
year 2020	-0.191***	-0.0369***	-0.654***
	(0.0339)	(0.0111)	(0.0837)
Only IoT * year 2020	0.0628	0.0200	-0.824
	(0.0885)	(0.0311)	(0.699)
# tech 2-4 * year 2020	0.129***	0.0336***	0.221**
	(0.0295)	(0.0127)	(0.108)
# tech $\geq$ 5 * year 2020	0.147***	0.0632***	0.272**
	(0.0312)	(0.0122)	(0.126)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	14.66***	2.031***	7.999***
	(0.469)	(0.222)	(1.044)
N of Obs	22466	22466	22466
N of firms	4516	4516	4516
R^2	0.164	0.463	0.055

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). The control group includes firms that did not adopt any digital technology in 2016-2017. The discrete treatment variable is defined in three categories: # tech 1 if the firm adopted only the focus technology; #tech 2-4 if the firm adopted the focus technology together with at least another digital technology and at maximum with other three technologies; #tech $\geq$ 5 if the firm adopted the focus technology with at least other four different technologies. Clustered robust standard errors (at firm level) in parentheses.

Table E.2: 3D Printing discrete Diff-in-Diff by number of technologies adopted in bundles

	Turnover	Employment	Productivity
year 2020	-0.202***	-0.0298**	-0.387**
	(0.0687)	(0.0136)	(0.155)
Only 3D Printing * year 2020	-0.0100	0.0405*	-0.850
	(0.111)	(0.0215)	(0.792)
# tech 2-4 * year 2020	0.0356	0.0203	0.122
	(0.0510)	(0.0153)	(0.187)
# tech $\geq$ 5 * year 2020	0.0141	0.0141	0.112
	(0.0520)	(0.0117)	(0.213)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	12.04***	1.324***	12.98***
	(1.439)	(0.298)	(1.965)
N of Obs	6451	6451	6451
N of firms	1294	1294	1294
R^2	0.296	0.613	0.081

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). The control group includes firms that did not adopt any digital technology in 2016-2017. The discrete treatment variable is defined in three categories: # tech 1 if the firm adopted only the focus technology; #tech 2-4 if the firm adopted the focus technology together with at least another digital technology and at maximum with other three technologies; #tech ≥ 5 if the firm adopted the focus technology with at least other four different technologies. Clustered robust standard errors (at firm level) in parentheses.

Table E.3: Robotics discrete Diff-in-Diff by number of technologies adopted in bundles

	Turnover	Employment	Productivity
year 2020	-0.153***	0.00890	-0.344***
	(0.0392)	(0.0116)	(0.109)
Only Robotics * year 2020	0.0719	0.0154	0.573***
	(0.0440)	(0.0171)	(0.204)
# tech 2-4 * year 2020	0.0722***	0.0357***	0.322***
	(0.0218)	(0.00971)	(0.0976)
# tech $\geq$ 5 * year 2020	0.0539**	0.0263**	0.316**
	(0.0273)	(0.0103)	(0.133)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	14.45***	2.339***	12.46***
	(0.731)	(0.298)	(1.591)
N of Obs	11085	11085	11085
N of firms	2228	2228	2228
R^2	0.249	0.546	0.114

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). The control group includes firms that did not adopt any digital technology in 2016-2017. The discrete treatment variable is defined in three categories: # tech 1 if the firm adopted only the focus technology; #tech 2-4 if the firm adopted the focus technology together with at least another digital technology and at maximum with other three technologies; #tech $\geq$ 5 if the firm adopted the focus technology with at least other four different technologies. Clustered robust standard errors (at firm level) in parentheses.

Table E.4: CSMI Goods discrete Diff-in-Diff by number of technologies adopted in bundles

	Turnover	Employment	Productivity
year 2020	-0.188***	-0.0346***	-0.569***
	(0.0224)	(0.00825)	(0.0641)
Only CSMI Goods * year 2020	0.0555	0.0367**	-0.110
	(0.0556)	(0.0157)	(0.193)
# tech 2-4 * year 2020	0.0989***	0.0539***	0.296***
	(0.0216)	(0.00780)	(0.0729)
# tech $\geq$ 5 * year 2020	0.120***	0.0647***	0.147
	(0.0266)	(0.00977)	(0.117)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	13.73***	1.564***	5.983***
	(0.792)	(0.232)	(1.955)
N of Obs	36195	36195	36195
N of firms	7282	7282	7282
R^2	0.147	0.459	0.045

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). The control group includes firms that did not adopt any digital technology in 2016-2017. The discrete treatment variable is defined in three categories: # tech 1 if the firm adopted only the focus technology; #tech 2-4 if the firm adopted the focus technology together with at least another digital technology and at maximum with other three technologies; #tech $\geq$ 5 if the firm adopted the focus technology with at least other four different technologies. Clustered robust standard errors (at firm level) in parentheses.

Table E.5: Cloud Computing discrete Diff-in-Diff by number of technologies adopted in bundles

	Turnover	Employment	Productivity
year 2020	-0.208***	-0.0566***	-0.589***
	(0.0204)	(0.00766)	(0.0649)
Only Cloud Computing * year 2020	0.00153	0.0252	-0.234
	(0.0675)	(0.0206)	(0.230)
# tech 2-4 * year 2020	0.110***	0.0358***	0.227***
	(0.0217)	(0.00882)	(0.0823)
# tech ≥ 5 * year 2020	0.166***	0.0653***	0.254**
	(0.0277)	(0.0105)	(0.121)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	13.46***	1.804***	7.922***
	(0.466)	(0.202)	(1.232)
N of Obs	45389	45389	45389
N of firms	9140	9140	9140
R^2	0.153	0.461	0.029

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). The control group includes firms that did not adopt any digital technology in 2016-2017. The discrete treatment variable is defined in three categories: # tech 1 if the firm adopted only the focus technology; #tech 2-4 if the firm adopted the focus technology together with at least another digital technology and at maximum with other three technologies; #tech ≥ 5 if the firm adopted the focus technology with at least other four different technologies. Clustered robust standard errors (at firm level) in parentheses.

Table E.6: Apps discrete Diff-in-Diff by number of technologies adopted in bundles

	Turnover	Employment	Productivity
year 2020	-0.245***	-0.0682***	-0.681***
	(0.0196)	(0.00663)	(0.0595)
Only Apps * year 2020	-0.0576	-0.0206	-0.222
	(0.0521)	(0.0164)	(0.192)
# tech 2-4 * year 2020	0.0973***	0.0355***	0.204***
	(0.0178)	(0.00816)	(0.0750)
# tech $\geq$ 5 * year 2020	0.157***	0.0704***	0.309***
	(0.0262)	(0.0100)	(0.113)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	13.08***	1.632***	6.921***
	(0.445)	(0.216)	(1.605)
N of Obs	58958	58958	58958
N of firms	11866	11866	11866
R^2	0.167	0.440	0.035

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). The control group includes firms that did not adopt any digital technology in 2016-2017. The discrete treatment variable is defined in three categories: # tech 1 if the firm adopted only the focus technology; #tech 2-4 if the firm adopted the focus technology together with at least another digital technology and at maximum with other three technologies; #tech ≥ 5 if the firm adopted the focus technology with at least other four different technologies. Clustered robust standard errors (at firm level) in parentheses.

Table E.7: Big Data Analytics discrete Diff-in-Diff by number of technologies adopted in bundles

	Turnover	Employment	Productivity
year 2020	-0.198***	-0.00445	-0.331***
	(0.0526)	(0.0128)	(0.111)
Only Big Data Analytics * year 2020	-0.308	-0.0829	-1.945
	(0.218)	(0.127)	(1.452)
# tech 2-4 * year 2020	0.102***	0.0131	0.0580
	(0.0390)	(0.0159)	(0.185)
# tech $\geq$ 5 * year 2020	0.0746*	0.0353**	-0.231
	(0.0393)	(0.0158)	(0.188)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	13.69***	2.233***	8.269***
	(0.771)	(0.289)	(1.652)
N of Obs	13606	13606	13606
N of firms	2738	2738	2738
R^2	0.172	0.526	0.037

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). The control group includes firms that did not adopt any digital technology in 2016-2017. The discrete treatment variable is defined in three categories: # tech 1 if the firm adopted only the focus technology; #tech 2-4 if the firm adopted the focus technology together with at least another digital technology and at maximum with other three technologies; #tech $\geq$ 5 if the firm adopted the focus technology with at least other four different technologies. Clustered robust standard errors (at firm level) in parentheses.

Table E.8: Augmented Reality discrete Diff-in-Diff by number of technologies adopted in bundles

	Turnover	Employment	Productivity
year 2020	-0.0513	-0.00984	-0.358*
	(0.0701)	(0.0263)	(0.197)
Only Augmented Reality * year 2020	0.0900	0.131**	-0.0601
	(0.151)	(0.0584)	(0.226)
# tech 2-4 * year 2020	0.114	0.0652**	0.144
	(0.0753)	(0.0318)	(0.240)
# tech $\geq$ 5 * year 2020	0.0530	0.0294	0.182
	(0.0614)	(0.0256)	(0.278)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	14.68***	2.109***	12.08***
	(0.697)	(0.293)	(2.244)
N of Obs	4139	4139	4139
N of firms	832	832	832
R^2	0.135	0.588	0.121

Source: our calculations on Istat data. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). The control group includes firms that did not adopt any digital technology in 2016-2017. The discrete treatment variable is defined in three categories: # tech 1 if the firm adopted only the focus technology; #tech 2-4 if the firm adopted the focus technology together with at least another digital technology and at maximum with other three technologies; #tech $\geq$ 5 if the firm adopted the focus technology with at least other four different technologies. Clustered robust standard errors (at firm level) in parentheses.

F The Role of Adopting Any Digital Technology

Table F.1: Prior adoption of at least one digital technology vs. Non-adopters

	Turnover	Employment	Productivity
year 2020	-0.149***	-0.0297***	-0.566***
	(0.0170)	(0.00703)	(0.0618)
Treatment * year 2020	0.0734***	0.0296***	0.242***
	(0.0166)	(0.00712)	(0.0716)
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	13.96***	2.049***	5.652***
	(0.443)	(0.175)	(1.586)
N of Obs	47197	47197	47197
N of firms	9552	9552	9552
R^2	0.128	0.438	0.039

Source: our calculations on Istat data. Treatment group is a randoms stratified sample of the 50% of the treatment group. Stratification of the sample conducted on 2-digit NACE, region and size classes. Other controls include: lag of employment, workforce composition (education, age, gender, seniority, profession, contractual category), firm's productive characteristics (2-digits NACE code, NUTS 2 regions, age, international markets, multinationals, groups). Clustered robust standard errors (at firm level) in parentheses.