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RESEARCH ARTICLE

Is this time different? How Industry 4.0 affects firms' labor productivity

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Abstract Does Industry 4.0 technology adoption push firms' labor productivity? We contribute to the literature debate—mainly focused on robotics and large firms—by analyzing adopters' labor productivity returns when micro, small, and medium enterprises (MSME) are concerned. We employ original survey data on Italian MSMEs' adoption investments related to a multiplicity of technologies and rely on a difference-in-differences estimation strategy. Results highlight that Industry 4.0 technology adoption leads to a 7% increase in labor productivity. However, this effect decreases over time and is highly heterogeneous with respect to the type, the number, and the variety of technologies adopted. We also identify potential channels explaining the labor productivity returns of technology adoption: cost-related efficiency, new knowledge creation, and greater integration/collaboration both within the firm and with suppliers.

Plain English Summary Becoming Industry 4.0 technology adopter boosts Italian manufacturing micro, small, and medium enterprises' (MSME) labor productivity by more than 7% on average. This is the key finding of new research based on original survey data collected from a sample of MSMEs operating in "Made in Italy" industries. Specifically, the research suggests that brand-new adopters of Industry 4.0 technologies gain a labor productivity premium compared to their non-adopting counterparts that lasts for up to 2 years after the adoption occurred. However, the productivity returns of technology adoption show non-linearities with respect to both the number of new technologies adopted by the firm and the variety of "technology groups" (production, customization, and data processing technologies). Overall, these results point to the relevance of industrial policies promoting the adoption of Industry 4.0 technologies by MSMEs, and this seems to be particularly the case for all those countries where MSMEs make the bulk of the national industrial system.

Keywords Technology adoption · Labor productivity · MSME · Industry 4.0 · Italy

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1 Introduction

Industry 4.0 promises to transform several business processes, especially in the manufacturing industry (Frank et al., 2019). Technologies such as 3D printing, advanced robotics, Internet of Things (IoT), big data and analytics, and augmented/virtual reality (Dalmarco et al., 2019; Lee et al., 2018) have the potential to affect manufacturing processes, from product innovation and prototyping to the organization of production activities (Büchi et al., 2020; Schrauf & Berttram, 2016), with positive effects on labor productivity (Kromann et al., 2020).

The analysis of the relationship between technology and labor productivity is not new. Indeed, the economics literature has widely emphasized how digital technology fosters labor productivity (Bloom et al., 2012; Brynjolfsson & Hitt, 2003; Jorgenson et al., 2008; Stiroh, 2002). However, most studies focus on Information and Communication Technology (ICT) and robotics and rely mainly on aggregate (industry-level) data to analyze the different elasticity between technology versus non-technology capital, and their relative contribution to Total Factor Productivity (TFP) growth. By contrast, only few studies have adopted a micro-level perspective to analyze how technology can spur labor productivity at the firm level (Bartel et al., 2007; Chen & Lien, 2013; Hofmann & Orr, 2005; Stoneman & Kwon, 1996), and even less evidence exists on micro, small, and medium enterprises (MSME) specialized in manufacturing activities (Cirillo et al., 2023; Díaz-Chao et al., 2015; Hwang & Kim, 2022).

We contribute to cover this gap in the literature by analyzing MSMEs' labor productivity returns of Industry 4.0 technology adoption. Our contribution is threefold. First, we add to the existing literature on MSMEs' labor productivity that has considered exclusively the role of ICT (e.g., Díaz-Chao et al., 2015) by analyzing the portfolio of Industry 4.0 technologies. Second, we complement previous studies focused on robotics and large firms (e.g., Acemoglu et al., 2020; Graetz & Michaels, 2018; Jungmittag & Pesole, 2019; Kromann et al., 2020) with novel evidence on the effect of a multiplicity of Industry 4.0 technologies on MSMEs' labor productivity. Finally, we provide a novel and more nuanced understanding of the labor productivity returns of Industry 4.0 by accounting for both additive and variety effects related to technology adoption over time based on detailed information on the year of adoption.

We focus on manufacturing MSMEs in Northern Italy, i.e., the area of the country characterized by the highest concentration of manufacturing firms. Indeed, Italy is among the most important manufacturing countries worldwide, and its industrial structure is mainly driven by MSMEs.[1] Moreover, the Italian government promoted in 2016 the "National Plan for Industry 4.0" to provide financial support and fiscal incentives to spread the adoption of Industry 4.0 technologies among manufacturing firms. We use original firm-level data derived from a survey we conducted on MSMEs in 2017 to collect information on the type of Industry 4.0 technology adopted and the year of first adoption, if any, and we enrich the survey-based data with balance sheet figures of the surveyed firms covering the period 2010–2017.

We rely on a staggered difference-in-differences estimation approach to identify the causal effect of new technology adoption on labor productivity. Our results suggest that the adoption of Industry 4.0 technologies has an overall positive and economically relevant effect on MSMEs' labor productivity, as we estimate a 7.4% increase in labor productivity related to new technology adoption. However, we also find that this effect decreases over time, with a peak of return 2 years after the adoption occurred. We also find non-linear effects related to both the number and the variety of Industry 4.0 technologies adopted. Finally, we provide evidence on the mechanisms underlying the labor productivity returns of new technology adoption. We find that, among adopters, Industry 4.0 technologies tend to increase efficiency in the production process, contribute to generate new knowledge improving both the production process and the products, and favor both greater integration

[1] MSMEs contribute to 66.9% of the overall value added in the Italian non-financial business sector, and their share of generated employment equals to 78.1%. These values are particularly large, especially when compared with European Union (EU) figures. Indeed, the EU average contribution of MSMEs to value added in the non-financial business sector equals to 56.4%, while it equals to 66.6% in the case of employment (European Commission, 2019).

among a firm's internal functions and greater collaboration between a firm's production function and its suppliers.

Our analysis has relevant implications for both practitioners and policymakers. Indeed, our results suggest that MSMEs may benefit from the positive labor productivity returns of technological investment, such that policymakers should design and implement industrial policies to support MSMEs' technology adoption and technological transformation.

The rest of the paper is structured as follows. Section 2 presents the theoretical framework and the literature related to the topic. Section 3 presents the data, the empirical modeling, and the econometric strategy. Section 4 presents the results. Section 5 provides evidence on the underlying mechanisms. Section 6 concludes by discussing the main findings and drawing some policy implications.

2 Theoretical background

2.1 Enhancing productivity in manufacturing firms: three mechanisms of Industry 4.0

Industry 4.0 is changing how business processes are organized (Nanry et al., 2015; Porter & Heppelmann, 2014), and manufacturing is considered not only as one of the epicenters of this transformation (Schwab, 2017) but also as one of the economic sectors that could benefit the most from the adoption of Industry 4.0 technologies in terms of productivity and global competitiveness (Almada-Lobo, 2015). The general idea underlying Industry 4.0 is the possibility to increase product customization without decreasing production efficiency in manufacturing firms (Brynjolfsson & McAfee, 2012).

There is a not a widely accepted definition of what should be considered as Industry 4.0. The concept itself has been coined in Germany to define a new industrial policy for promoting innovation and competitiveness in the manufacturing industry (Kagermann et al., 2013). Thus, the concept emerged for a more comprehensive definition of cyber and physical systems as a combination of digital tools and physical machines. Since this first German elaboration, the concept has been backed by the most important global consulting firms (Deloitte, 2015; Dujin et al., 2014; Nanry et al., 2015; Rüßmann et al., 2015) and has been used to define a new technological paradigm for (manufacturing) firms. Moreover, the literature provides different interpretations of this concept using definitions such as "smart factory" (Kagermann, 2015; Kusiak, 2018; Lu & Weng, 2018; Mittal et al., 2019; Thoben et al., 2017), "smart manufacturing" (Hozdić, 2015; Jung et al., 2017; Mittal et al., 2018; Prause, 2019), "digital manufacturing" (Byrne et al., 2016; Cavalcante et al., 2019; Chen et al., 2015), "cyber physical systems" (Agostini & Filippini, 2019; Müller, 2019; Müller et al., 2018; Schlechtendahl et al., 2015), and "Industrial IoT" (Arnold et al., 2016; Arnold & Voigt, 2019; Kiel et al., 2017).

Despite these definitional differences, the literature agrees on the key novelty characterizing the Industry 4.0 technological revolution, i.e., the possibility for a firm to exploit the benefits of interconnection among the individual adopted technologies, with its overall information system and within its network of relationships (Culot et al., 2020). Therefore, Industry 4.0 comes as an "agglomeration" of different technologies that are conveniently clustered together by technology providers, system integrators, consultants, and policymakers, and these "clusters of technologies" can also be modified in relation to the emergence of some new technological solutions—as an example, artificial intelligence is now considered as one of the pillars of Industry 4.0 (Martinelli et al., 2021) despite it was not included in its first elaboration (Rüßmann et al., 2015).

But how can Industry 4.0 technologies affect firm labor productivity? We can outline three main mechanisms through which such technologies can translate into higher labor productivity for adopting firms. The first mechanism mainly runs through production efficiency. In this sense, automation of production, through robotics, can speed up production processes improving the use of inputs and materials, lowering (unexpected) costs as well as waste (Acemoglu et al., 2020; Cimini et al., 2021). Moreover, thanks to the new flexibility of robots, it is now possible to automatize more complex activities without decreasing the overall quality of production, as well as to switch easier and faster the assembly line across alternative products. Robotics allows for greater efficiency of the manufacturing process (Ballestar et al., 2021) and, consequently, greater labor productivity.

The second mechanism concerns the possibility of innovating production processes and products (Porter & Heppelmann, 2014) through the digitalization of different stages of the production process, also in relation to product design (e.g., 3D printing), where the production of physical products is driven by digital information. Digitalization facilitates the manufacture of parts and components that are difficult to produce (e.g., due to a peculiar geometry) by innovating the production process.[2] In this regard, digitalization is likely to increase labor productivity thanks to process innovation, which helps in reducing the unitary time-length of production (Dujin et al., 2014; Wimpenny et al., 2017).

Finally, Industry 4.0 can contribute in increasing labor productivity by facilitating integration and communication among production stages and the different business functions of the firm (Bartel et al., 2007; Bettiol et al., 2023; Chen & Lien, 2013; Hofmann & Orr, 2005; Stoneman & Kwon, 1996) through an improved data analysis (Davenport et al., 2020).

2.2 Industry 4.0 technologies and MSMEs' labor productivity

There is a growing number of empirical studies analyzing whether and to what extent the adoption of Industry 4.0 technologies affects firms' performance in general and labor productivity in particular. However, the literature has focused mainly on robotics without analyzing neither other types of Industry 4.0 technologies nor the effects related to their combined adoption by firms. Moreover, previous contributions analyzing the role of technology adoption on labor productivity have focused almost exclusively on large firms, thus neglecting potential efficiency gains for MSMEs.

Empirical evidence supports the theoretical mechanisms previously highlighted through which Industry 4.0 technologies foster labor productivity at the firm level. For example, Graetz and Michaels (2018) estimate that robotics leads to a 0.36 percentage points increase in annual labor productivity growth. A similar result is found by Jungmittag and Pesole (2019) when analyzing the impact of robotics in Europe and by Acemoglu et al. (2020) in the case of French firms. More generalized evidence is provided by Kromann et al. (2020), who estimate a strong positive effect of robotics on the labor productivity and TFP of European, US, and Japanese firms.

Such analyses consider mainly large firms. Indeed, when it comes to the context of MSMEs, most research has focused on production-based (i.e., cost reduction and speed) and/or marketing-oriented (i.e., flexibility, customization, and service) outcomes (e.g., Büchi et al., 2020; Dalenogare et al., 2018; Frank et al., 2019), while very little attention has been paid on how Industry 4.0 can affect MSMEs' labor productivity—examples are Díaz-Chao et al. (2015), who consider exclusively ICT; Cirillo et al. (2023), who analyze firm size heterogeneity; and Hwang and Kim (2022), who estimate an average 26% productivity premium for Korean manufacturing small and medium firms adopting new technologies compared to their non-adopting counterparts.

Structural differences between large firms and MSMEs prevent us from generalizing large firm-based evidence of positive productivity returns of technology adoption to the context of MSMEs. Indeed, MSMEs are, by definition, smaller and endowed with less human and physical capital resources than large firms. They are also less innovative and tend to benefit from internationalization advantages to a much lower extent than large companies (Pellegrino & Zingales, 2017; Zeli et al., 2022). Moreover, they are less prone to adopt a new technology as they tend to lack both the financial resources needed to acquire it—indeed, they tend to both have less available internal financial resources and be more credit rationed by banks than large firms (Aristei & Angori, 2022; Ganau & Rodríguez-Pose, 2022)—and the internal workforce needed to integrate it into the production process.

Nevertheless, new technology adoption can provide MSMEs with substantial performance gains similar to large firms. Indeed, Industry 4.0 technologies can lead to a radical shift in the production structure of the adopting MSME by offering the

[2] For example, Rolls-Royce uses 3D printing technology to produce components for its jet engines in order to reduce production time through substitution of some components that otherwise have very long lead times due to the tooling process (Dujin et al., 2014; Wimpenny et al., 2017). In the automotive industry, 3D printing could help companies to decrease the spare parts warehouses. Instead of storing an already produced component of the car, the 3D printer could produce it when the spare part is needed, thus leading to lowered costs and improved production efficiency (Nichols, 2019).

same advantages of large firms in terms of speeding the production process, lowering costs, and improving the efficiency of the overall internal organization (Bloom et al., 2012). In other words, MSMEs adopting new technologies are likely to gain in terms of labor productivity increases as large firms do.

It thus becomes essential to assess empirically whether Industry 4.0 technology can represent a key productivity-enhancing factor for MSMEs, in the same way as existing empirical evidence suggests it is for large firms. We explicitly aim at understanding if this is the case, i.e., whether and to what extent MSMEs adopting Industry 4.0 technologies record a labor productivity premium with respect to their non-adopting counterparts. We do this by proxying Industry 4.0 through a multiplicity of technologies, besides robotics.

2.3 Groups of Industry 4.0 technologies, variety, and non-linearity

Scholars have recently shown that Industry 4.0 technologies could be clustered into "groups" based on their use and impacts (Bettiol et al., 2022; Culot et al., 2020; Frank et al., 2019; Zheng et al., 2021), namely: (i) technologies adopted to improve operations and working-related activities, such as advanced robotics and augmented reality (Frank et al., 2019; Ghobakhloo, 2018); (ii) technologies adopted to improve flexibility and allowing for customization (Weller et al., 2015), such as additive manufacturing (D'Aveni, 2015) and other flexible machineries and tools to support digital manufacturing (Ardanza et al., 2019); and (iii) technologies related to data processing, such as cloud, big data analysis, and IoT solutions (Klingenberg et al., 2021), which are strictly related to the concept of "smart factory" (Strozzi et al., 2017).

Due to the intricate and diverse nature of Industry 4.0 technologies, there exists evidence suggesting that organizations may opt to implement technologies from different groups based on the anticipated benefits associated with each group. Empirical evidence suggests that firms tend to select technologies from one group over another (e.g., Dalenogare et al., 2018; Frank et al., 2019). Recent literature has also emphasized the importance of considering not only the number of technologies adopted but also the variety of technologies in relation to the specific group under consideration when assessing the impact of Industry 4.0 (e.g., Büchi et al., 2020; Culot et al., 2020).

Moreover, as shown in the innovation literature (e.g., Rosenberg, 2010), more than linearity is at stake in the adoption of new technologies. Despite intense research on the association between Industry 4.0 technology and firm performance, the impact of new technology investment remains still unclear due to the non-linear relationship between Industry 4.0 technology adoption and performance (Lau & Bendig, 2022). For example, Wang et al. (2017) find that the adoption of advanced robotics and 3D printing allows manufacturing firms to move into a mass customization strategy which, in turn, allows to achieve benefits in terms of efficiency and flexibility. Moreover, through the adoption of advanced manufacturing and data processing technologies (e.g., augmented reality, big data and cloud, and IoT), a firm can both increase productivity and develop new products and services (Lee & Lee, 2015). At the same time, evidence shows that the adoption of several technologies could increase complexity, thus leading to an inverted U-shaped relationship with business performance (Cheah et al., 2021).

We exploit the fact that different Industry 4.0 technologies present strong complementarities to analyze explicitly both whether "more is better"—i.e., whether a non-linearity driven by multiple adoption exists—and whether "diversified is better"—i.e., whether there exists a labor productivity premium associated with the combined adoption of a variety of different technologies.

Furthermore, we examine an under-researched topic in the existing literature, namely, the potential temporal variation in the impact of Industry 4.0 technologies on productivity assessed through the time of first adoption.

3 Data and methodology

3.1 The dataset

We analyze the firm-level labor productivity returns of new technology adoption by relying on the survey data we collected to target Italian manufacturing MSMEs located in Northern Italy. We focused the survey on firms operating in "Made in Italy" industries (i.e., home furnishings, mechanics, and fashion) located in the regions of Piedmont, Lombardy, Veneto, Trentino-South Tyrol, Friuli-Venezia Giulia, and Emilia Romagna. We started from a population of 7714 manufacturing firms drawn from the Aida database (Bureau van Dijk), which provides comprehensive balance sheet figures, as well as information on location and industry, for Italian companies. We sampled firms with a 2015 turnover value higher than 1 million Euros. For some industries (e.g., lighting, eyewear, jewelry, and sport equipment) characterized by a large presence of industrial districts where even micro and small firms can be competitive due to the high specialization within the local value chain (Becattini et al., 2009), we also selected firms with a 2015 turnover value lower than 1 million Euros. We submitted a structured questionnaire to either entrepreneurs, chief operation officers, or managers in charge of manufacturing and technological processes of all the sampled firms through a computer-assisted web interview (CAWI) methodology. The interview process resulted in a 15.9% response rate, corresponding to 1229 firms which provided us with usable information. We selected key Industry 4.0 technologies to gather information on following previous studies (Agostini & Nosella, 2020; Frank et al., 2019; Vajjhala & Ramollari, 2016) and, especially, focusing on the peculiarities of the Italian manufacturing context (Bonfanti et al., 2018; Zheng et al., 2020) and the relevance of intelligent machine tools (Huang et al., 2019; Tong et al., 2020) for the digital transformation of "Made in Italy" industries (Bonfanti et al., 2018; Di Roma, 2017). We thus asked surveyed firms about the adoption of the following technologies: (i) advanced robotics; (ii) additive manufacturing; (iii) laser cutting; (iv) big data and cloud; (v) 3D scanner; (vi) augmented reality; and (vii) IoT and smart products. We collected information not only on the individual technologies adopted, if any, but also on the year each technology has been adopted for the very first time.

We then complemented survey-based information on firms' technology adoption with balance sheet data of the respondent firms directly drawn from the Aida database. First, we cleaned the sample of 1229 respondent firms—having excluded a priori uncompleted questionnaires characterized by missing responses on the year of first-time technology adoption—to include only firms reporting positive and reliable figures for value added, employment, wages and salaries, and tangible fixed assets for the period 2010–2017. The rationale for analyzing labor productivity over the period 2010–2017 is twofold. First, we run the interview in December 2017, such that this is the last year for which we have information on technology adoption. Second, the Italian economy has been hit by the 2008 Great Recession between the first quarter of 2008 and the second quarter of 2009, and it has started to recover only between the third quarter of 2009 and the first quarter of 2010, such that inclusion of the years 2008–2009 could potentially bias the results due to abnormal, crisis-related effects.[3] Second, we excluded from the sample firms without information on the year of incorporation. Finally, we excluded firms that have adopted at least one Industry 4.0 technology for the first time before the year 2010: this allows us to assess the labor productivity returns of technology adoption for firms that have adopted a technology for the very first time in the period 2010–2017 compared to firms that have never adopted an Industry 4.0 technology either before 2010 or in the period 2010–2017. The cleaning procedure left us with a final sample of 907 firms observed over the period 2010–2017, for a total of 6460 firm-year observations.

The sample includes firms located in the North-Eastern regions of Emilia Romagna (13.2%), Friuli-Venezia Giulia (2.7%), Trentino-South Tyrol (1.4%), and Veneto (35.3%), as well as firms located in the North-Western regions of Lombardy (34.4%) and Piedmont (13.0%) (Supplementary Table S1). Overall, the sample includes 79 MSMEs that have adopted at least one Industry 4.0 technology during the period 2010–2017 (Supplementary Table S2). Among adopters, micro firms (1 to 9 employees) represent 25.3%, and small firms (10 to 49 employees) represent 54.4% while medium firms (50 to 249 employees) represent 20.3%.[4] Overall, micro firms represent 27.9% of the

[3] According to Eurostat data, the Italian Gross Domestic Product (expressed in current market prices and seasonally and calendar adjusted) dropped by 5.1% between the first quarter of 2008 and the second quarter of 2009—the time span generally regarded as the crisis period for Europe; it recorded a 0.7% increase between the third quarter of 2009 and the first quarter of 2010; and it increased by 10.8% between the first quarter of 2010 and the fourth quarter of 2017.

[4] Size classes for micro, small, and medium firms are defined according to the European Commission Recommendation of 6 May 2003. For the purpose of firm classification, we consider employment values averaged over the period 2010–2017.

sample, small firms represent 60.4%, and medium firms represent 11.7% (Supplementary Table S3).

3.2 The empirical model

We consider a firm-level Cobb-Douglas production function with constant returns to scale that we can express in per employee terms as follows:

$$\frac{Y_{it}}{L_{it}} = A_{it}\left(\frac{K_{it}}{L_{it}}\right)^{\alpha} \tag{1}$$

where labor productivity of firm i at time t (Y_{it}/L_{it}) is defined as a function of efficiency (A_{it}) and the physical capital-to-labor ratio (K_{it}/L_{it}), with physical capital and labor force denoted by K_{it} and L_{it}, respectively.

We hypothesize that new technology adoption influences both technical and non-technical firm-level labor productivity parameters and specify the parameter A_{it} as a linear combination of firm-specific capabilities (F_{it})—e.g., productive efficiency, managerial competences, and accumulated know-how—and the new technology (T_{it}) entering the production process, such that

$$A_{it} = g\left(F_{it}, T_{it}\right) \tag{2}$$

where the effect associated with the new technology is assumed to depend simply on its adoption, such that $T_{it} = e^{\lambda TA_{it}}$, where TA_{it} is an indicator variable capturing the adoption of a new technology by firm i at time t, and the parameter λ captures the effect of adoption with respect to non-adoption.[5] By combining Eqs. (1) and (2) and taking logarithms, we obtain the following functional form:

$$\log\left(\frac{Y_{it}}{L_{it}}\right) = \log\left(F_{it}\right) + \log\left(e^{\lambda TA_{it}}\right) + \alpha\log\left(\frac{K_{it}}{L_{it}}\right) \tag{3}$$

In order to estimate Eq. (3), the firm-specific capabilities term can be expressed as a linear combination of a constant term (β_0), firm-specific fixed effects (γ_i), time-specific fixed effects (δ_t), and an error component (ε_{it}), such that $\log(F_{it}) = \beta_0 + \gamma_i + \delta_t + \varepsilon_{it}$. We can thus re-specify Eq. (3) as follows:

$$\log\left(\frac{Y_{it}}{L_{it}}\right) = \beta_0 + \gamma_i + \delta_t + \lambda TA_{it} + \alpha\log\left(\frac{K_{it}}{L_{it}}\right) + \varepsilon_{it} \tag{4}$$

Equation (4) can be further augmented with a set of firm-specific time-varying controls, plus industry- and region-level time trends, in order to reduce unobserved heterogeneity. By setting $\mathrm{LP}_{it} = Y_{it}/L_{it}$, we obtain the following empirical regression equation:

$$\begin{aligned}\log\left(\mathrm{LP}_{ijrt}\right) = \beta_0 + \lambda\mathrm{TA}_{ijrt} + \alpha\log\left(\frac{K_{ijrt}}{L_{ijrt}}\right) \\ + \sum_{g=1}^{G}\zeta_g X_{ijrt}^{g} + \gamma_i + \delta_t + \tau_{jt} + \tau_{rt} + \varepsilon_{ijrt}\end{aligned} \tag{5}$$

where the additional subscripts j and r denote industrial (at the two-digit level) and regional (at the province level) dimensions, respectively, with $j = 1, \ldots, J$ and $r = 1, \ldots, R$.[6] The key explanatory variable in Eq. (5) is TA_{ijrt}, that captures the first-time adoption of a new technology. This is a binary variable which takes value zero in all the observed years for firms that never adopted a new technology and in the years before the first adoption occurred for firms that at some point in time t have introduced an Industry 4.0 technology for the very first time; the variable, instead, takes value one in the first-adoption year and remains equal to one for the rest of the panel for firms that at some point in time t have adopted the technology for the first time. The term X_{ijrt}^{g} denotes a vector of firm-specific time-varying control variables; τ_{jt} captures an industry-level time trend, while τ_{rt} captures a region-level time trend.

Labor productivity is defined as value added over employment; physical capital is defined in terms of tangible fixed assets; the vector X_{ijrt}^{g} of firm-specific controls includes both continuous and discrete variables. Continuous variables are the logarithm of an age variable (AGE_{ijrt}), defined as the year of observation minus the year of a firm incorporation; and the logarithm of wages

[5] Kromann et al. (2020) consider a Cobb-Douglas production function augmented with the stock of industrial robots in an industry-country framework. We consider a firm-level framework where labor productivity is "shocked" by first-time technology adoption rather than by the stock of technologies (or robots) introduced in the production process.

[6] Industries are defined according to the Ateco 2007 classification of economic activities adopted by the Italian National Institute of Statistics (Istat) and corresponding to the NACE Rev. 2 classification adopted at the EU level. Provinces correspond to the level 3 of the *Nomenclature des Unités Territoriales Statistiques* (NUTS) adopted by the EU.

and salaries (WS_{ijrt}) per employee ($\mathrm{WS}_{ijrt}/L_{ijrt}$).[7] Discrete variables included are time-varying size dummies defined in terms of employment for micro, small, and medium firms. We report some descriptive statistics of the dependent and explanatory variables in Supplementary Table S4 and the correlation matrix of explanatory variables in Supplementary Table S5.

3.3 Estimation strategy

We assess the effect of new technology adoption on firm-level labor productivity relative to firms which did not adopt a new technology by relying on a difference-in-differences estimation approach. Our identification strategy relies on the information on the exact year surveyed firms have adopted an Industry 4.0 technology for the very first time. As previously highlighted, we have cleaned the sample by excluding firms that have adopted an Industry 4.0 technology for the first time before the year 2010—i.e., the first year we observe firms' labor productivity—such that we can identify the causal effect of new technology adoption by comparing firms that have adopted an Industry 4.0 technology for the very first time in the period 2010–2017 with those that have never adopted an Industry 4.0 technology either before 2010 or in the period 2010–2017. In other words, we compare adopters and non-adopters conditional on non-adoption of an Industry 4.0 technology before 2010. This allows us to assess whether the brand-new introduction of an Industry 4.0 technology in the production process fosters labor productivity.

However, our estimates could still be biased due to potential endogeneity of the technology adoption choice. In fact, technology adoption is a non-random decision that could depend on firm-specific characteristics, as well as industry- and local-specific dynamics. We relax this issue by, first, including firm-level fixed effects (γ_i) in Eq. (5) to control for firm-specific unobserved conditions that could influence a firm's decision to adopt a new technology. Second, we account for industry-specific factors related to technology adoption through the industry-level time trend (τ_{jt}). Third, we account for conditions that are specific to the local productive system where firms are located and operate (e.g., inter-firm externalities, cooperation and/or competition mechanisms) and that could influence new technology adoption decisions through the region-level time trend (τ_{rt}).

We also test explicitly for the direction of causality between technology adoption and labor productivity within an event study framework to evaluate the comparability of adopters and non-adopters in the period before the first adoption occurred. We modify Eq. (5) by allowing the technology adoption variable to vary over time. We thus replace the variable TA_{ijrt} with a dummy variable (TA^*_{ijrt}) referring to the first-adoption year of a new technology, a full set of lead dummy variables (TA^*_{ijrt-l}) referring to each year before the first-adoption year, and a full set of lag dummy variables (TA^*_{ijrt+l}) referring to each year after the first-adoption year, with $l=1, \ldots, 7$ and TA^*_{ijrt-7} (TA^*_{ijrt+7}) denoting the maximum lead (lag) for a representative firm introducing a new technology in the year 2017 (2010), given $t=2010, \ldots, 2017$. This approach has two advantages. First, it allows us to check for anticipatory effects in terms of labor productivity levels, i.e., for differences in labor productivity between adopters and non-adopters in the period before the first-adoption year (Autor, 2003). Thus, we would expect insignificant estimated coefficients of the lead dummy variables if it is technology adoption to affect labor productivity, rather than the other way around. Second, it allows us to evaluate the temporal dynamics of new technology adoption, i.e., the time-varying effect (if any) of new technology adoption on labor productivity (Gustafsson et al., 2016). Formally, we modify Eq. (5) as follows:

$$\log\left(\mathrm{LP}_{ijrt}\right) = \beta_0 + \rho \mathrm{TA}^*_{ijrt} + \sum_{l=1}^{l=7} \rho_{-l}\mathrm{TA}^*_{ijrt-l} + \sum_{l=1}^{l=7} \rho_{+l}\mathrm{TA}^*_{ijrt+l} + \alpha \log\left(\frac{K_{ijrt}}{L_{ijrt}}\right) + \sum_{g=1}^{G} \zeta_g X^g_{ijrt} + +\gamma_i + \delta_t + \tau_{jt} + \tau_{rt} + \varepsilon_{ijrt} \tag{6}$$

and we estimate Eq. (6) by specifying the first-order lead dummy variable (TA^*_{ijrt-1}) as the reference category.

4 Results

4.1 Main results

Table 1 reports the results of the estimation of Eq. (5) with fixed effects, time trends, and firm-level controls

[7] The balance sheet figures for value added, wages and salaries, and tangible fixed assets are deflated at the industry level using data series provided by Eurostat.

Table 1 Technology adoption and labor productivity—main results

Dependent variable	$\log(LP_{ijrt})$							
Estimation method	Pooled OLS		FE					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TA_{ijrt}	0.146** (0.063)	0.148** (0.064)	0.091*** (0.034)	0.096*** (0.036)	0.098*** (0.035)	0.077** (0.033)	0.080** (0.035)	0.071** (0.029)
$\log(K_{ijrt}/L_{ijrt})$	…	…	…	…	…	0.102*** (0.015)	0.101*** (0.015)	0.035*** (0.012)
$\log(AGE_{ijrt})$	…	…	…	…	…	…	…	0.028 (0.034)
$\log(WS_{ijrt}/L_{ijrt})$	…	…	…	…	…	…	…	0.809*** (0.045)
$Micro_{ijrt}$	…	…	…	…	…	…	…	Ref.
$Small_{ijrt}$	…	…	…	…	…	…	…	−0.042* (0.024)
$Medium_{ijrt}$	…	…	…	…	…	…	…	−0.055 (0.038)
Industry × time trend	No	No	No	Yes	Yes	No	Yes	Yes
Region × time trend	No	No	No	No	Yes	No	Yes	Yes
Firm fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	6460	6460	6460	6460	6460	6460	6460	6460
No. of firms	907	907	907	907	907	907	907	907
R^2	0.003	0.005	0.687	0.696	0.697	0.698	0.707	0.801
Adjusted R^2	0.003	0.003	0.636	0.642	0.643	0.648	0.655	0.765
F statistics [p-value]	5.37 [0.021]	2.91 [0.003]	7.18 [0.008]	7.13 [0.008]	7.63 [0.006]	28.32 [0.000]	27.34 [0.000]	117.44 [0.000]

Robust standard errors are in parentheses

*$p<0.1$; **$p<0.05$; ***$p<0.01$

introduced according to a stepwise procedure. The simple Pooled Ordinary Least Squares (OLS) estimates suggest that new technology adoption is positively associated with labor productivity. Looking at specification (8), we estimate that, on average, new technology adoption increases MSMEs' labor productivity by about 7.4%. This result is in line with recent evidence on Italian firms provided by Cirillo et al. (2023), who estimate a 5% increase in labor productivity for technology adopters compared to non-adopting firms.

Having estimated a positive return of new technology adoption on firm-level labor productivity, we now test for the direction of causality. Figure 1 reports the key results obtained by estimating Eq. (6) and, specifically, plots the estimated coefficients of the dummy variables for first-adoption year and its leads and lags. First, it should be noted that none of the pre-adoption coefficients is statistically different from zero, meaning that the inclusion of firm-level control variables, together with sets of fixed effects and time trends, helps us in satisfying the parallel trend assumption. Second, Fig. 1 suggests that firms adopting a new technology experience an increase in labor productivity not only during the adoption year (by about 5.8%) but also 1 year after it (by about 6.1%). However, the positive returns of the new technology seem to become statistically negligible 2 years after the adoption occurred. This suggests that new technology adoption has a positive "shocking effect" on labor productivity, which, however, does not seem to be long-lasting.

Fig. 1 Technology adoption and labor productivity—event study design. Notes: The plot reports coefficients (90% confidence intervals) of leads and lags defined around the first-adoption year of a new technology. The reference period is set at $t-1$ with respect to the first-adoption year. The results are obtained through the two-way FE estimation of Eq. (6). Statistics of the estimated model: R^2 = 0.801; adjusted R^2 = 0.765; F [p-value] = 38.39 [0.000]

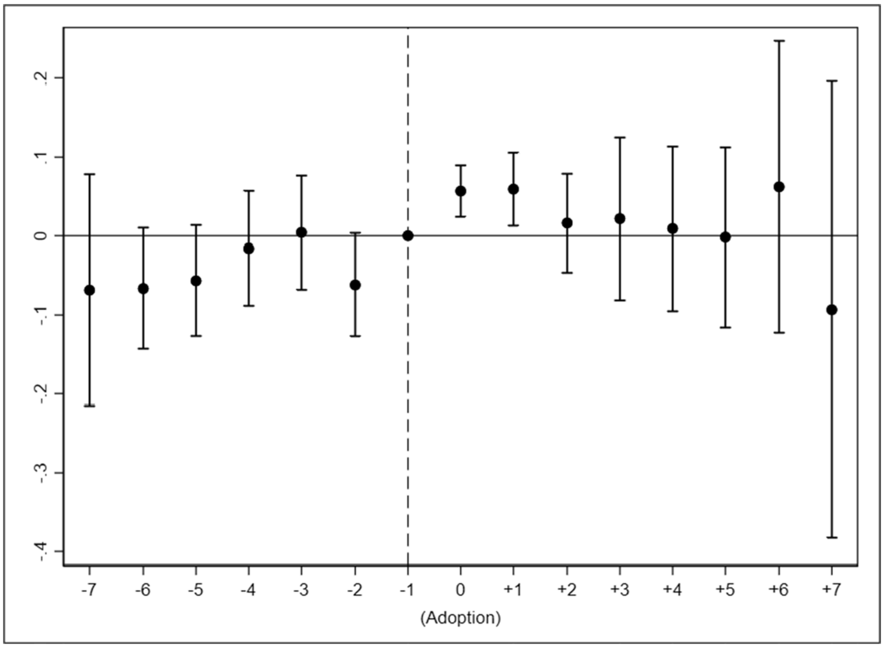

Table 2 Difficulties faced by adopters in implementing new technologies

Difficulty faced by adopters	Yes (%)	Yes (%) > 50% (p-value)
Lack of in-house expertise	87.30	0.000
Finding appropriate professional figures in the market	87.30	0.000
Limited financial resources to support the investment	85.71	0.000
Inadequate in-house information systems	87.30	0.000
Length of technology implementation process	88.89	0.000
Finding technology suppliers	87.30	0.000
Lack of broadband	84.13	0.000

Percentage values and statistical testing are based on 63 (out of 79) adopters for which survey information is available

This result may appear puzzling; however, there is a rationale behind it. Despite the fact that the adoption of new technologies is motivated by specific advantages (Dalenogare et al., 2018), firms often disregard the "hidden costs" associated with regular and exceptional maintenance, the expenses involved in technology upgrades (i.e., how the technology evolves), and other costs associated with organizational modifications. Indeed, as shown in Table 2, the majority of adopters in our estimation sample have faced difficulties related to technology adoption, such as the lack of in-house expertise or adequate information systems, the length of the implementation process, limited financial resources to support the technological investment or difficulties associated with finding technology suppliers, and appropriate professional figures in the market.[8] This could be particularly the case for MSMEs that are unaccustomed to frequent investments in new technologies and, consequently, lack related experience and managerial expertise.

[8] Survey information on a series of potential difficulties faced in adopting the new technologies is available only for 63 (out of the 79) technology adopters included in the sample. Due to the dichotomous nature of such information, we have performed a series of one-sample statistical tests to assess whether Industry 4.0 adopters who experienced such difficulties were a statistically significantly higher percentage than those who did not. In other words, we have tested the true distribution of adopters that faced difficulties in adopting technologies and those who did not against a hypothetical 50% distribution.

4.2 Robustness and falsification analyses

We now present robustness and falsification analyses aimed at assessing the sensitivity of our main results, while we report the results of these exercises in the Electronic Supplementary Material.

First, we rely on a Propensity Score Matching (PSM) approach to further minimize any potential bias related to the non-random, first-time adoption of a technology. We match firm-year observations on first-order time-lagged observable variables, having excluded from the analysis all firms for which the year 2010 (i.e., the first year of observation in the sample) corresponds to the very first time an Industry 4.0 technology is adopted. This exclusion criterion leaves us with 899 observed firms, for a total of 5502 firm-year observations. As a first exercise, we estimate the PSM through a logistic model controlling for the first-order time-lagged variables for capital-to-labor ratio, age, wages and salaries per employee, and size dummies, together with year, industry, and macro-region fixed effects. Second, we add the first-order time-lagged dependent variable for labor productivity to the set of explanatory variables in the logistic model. We impose a caliper of 0.0005 and select only matched firm-year observations lying on the common support. At this caliper, the similarity between adopters and non-adopters improves after the matching procedure (Supplementary Table S6). However, such exercises reduce the number of observations we can include in the estimation sample (Supplementary Table S7): the number of valid firm-year observations drops, in the first exercise, from 5502 to 4109 (i.e., 894 firms) and to 4108 (i.e., 892 firms) in the second exercise.[9] The results of these exercises confirm those presented in Table 1: new technology adoption leads to labor productivity increases, and we estimate a premium for adopters ranging between 6.3% and 7.5%, depending on the estimated specification (Supplementary Table S9).

Second, we replicate our baseline analysis by controlling for ICT adoption. We rely on survey information on whether a firm has adopted ICTs, and given the time-invariant nature of this information, we introduce the ICT dummy variable on the right-hand side of Eq. (5) by interacting it with year dummies. The results of this exercise are reported in specification (1) in Supplementary Table S10 and confirm the main ones. Third, we consider an industry-by-region time trend and, as shown in specification (2) in Supplementary Table S10, we still confirm the main results.

Fourth, we replicate our baseline analysis considering value added and employment as the dependent variables (Supplementary Table S11). We estimate a positive and statistically significant technology adoption coefficient in both cases, although the effect on value added is approximately 2.6 times larger in magnitude than that on employment. This evidence suggests that the estimated labor productivity premium for adopters is not the result of a "substitution effect" between technology and labor force; rather, it seems to be driven by an increase in efficiency that makes adopters relatively more efficient in generating value while, at the same time, experiencing an increase in the employment base. This result is consistent with Acemoglu et al. (2020), who find positive effects of robots' adoption on French firms' value added and total employment, besides TFP.

Finally, we run two placebo exercises to assess whether our main results are not an artifact of the small number of adopters in our dataset (Belloc et al., 2016; Chetty et al., 2009). First, we estimate Eq. (5) on 1000 randomly drawn placebo samples constructed by assigning the adoption status randomly, while keeping unchanged the true temporal structure of our dataset in terms of yearly number of first-time technology adoptions occurring. Indeed, our sample consists of 79 technology adopters, such that we assign the adoption status randomly to 79 firms at each draw but imposing the number of first-time adopters per year as for the real dataset. Second, we randomize on the adoption year rather than on firms. In this case, we estimate Eq. (5) on 1000 randomly drawn samples defined by assigning the year of first adoption randomly to the true 79 adopters in our dataset, but imposing the number of first-time adopters per year as for the real dataset. These two exercises allow us checking how many times the

[9] We have also considered similarity between adopters and non-adopters with respect to financial variables (EBITDA, return on assets, return of sales, return on equity) and did not find statistically significant mean differences (Supplementary Table S8).

randomly generated placebo coefficients are too close in magnitude to our true point estimate: indeed, we should observe placebo coefficients of our technology adoption variable close to our true estimated coefficient of 0.071 if we were rejecting the null hypothesis that our coefficient of interest is equal to zero erroneously. Figure S1 (Electronic Supplementary Material) plots the cumulative distribution of the coefficients obtained from the estimation of Eq. (5) on the two series of 1000 randomly drawn placebo samples. We find that the true estimated effect of technology adoption is always larger than the estimated placebo coefficients in both simulation exercises. Moreover, we find the placebo technology adoption coefficient to be statistically significant in 6.3% of occurrences when randomizing on the adoption status and in 4.5% of occurrences when randomizing on the first-time adoption year (Supplementary Table S12). Overall, these exercises corroborate our evidence of MSMEs gaining a labor productivity premium from Industry 4.0 technology adoption.

4.3 Further evidence

We now provide further evidence by evaluating the role of "technology groups" and individual technologies and by testing for effects related to the number and variety of technologies adopted.

First, we study "technology groups" and consider also individual technologies. Indeed, as discussed in Sub-section 2.3, Industry 4.0 technologies are not a homogenous cluster of technologies and are characterized by high variety. Surveyed firms were asked about the adoption of seven different technologies: augmented reality, robotics, additive manufacturing, 3D scanner, laser cutting, big data and cloud, and IoT.[10] Following Bettiol et al. (2022), we have clustered these technologies into three groups reflecting their functionality, namely: (i) production technologies (augmented reality, robotics); (ii) customization technologies (additive manufacturing, 3D scanner, laser cutting); and (iii) data processing technologies (big data and cloud, IoT).[11] We have thus modified

Table 3 Labor productivity effects of technology groups and individual technologies

Dependent variable	$\log(LP_{ijrt})$	
Estimation method	FE	
	(1)	(2)
Production technologies$_{ijrt}$	0.099** (0.048)	…
Robotics$_{ijrt}$	…	0.127** (0.063)
Augmented reality$_{ijrt}$	…	−0.198 (0.141)
Customization technologies$_{ijrt}$	0.082** (0.036)	…
Additive manufacturing$_{ijrt}$	…	−0.013 (0.069)
3D scanner$_{ijrt}$	…	−0.007 (0.072)
Laser cutting$_{ijrt}$	…	0.116* (0.070)
Data processing technologies$_{ijrt}$	0.060* (0.036)	…
Big data/cloud$_{ijrt}$	…	0.126* (0.072)
Internet of Things$_{ijrt}$	…	−0.043 (0.067)
Control variables	Yes	Yes
Industry × time trend	Yes	Yes
Region × time trend	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
No. of observations	6460	6460
No. of firms	907	907
R^2	0.763	0.828
Adjusted R^2	0.715	0.790
F statistics [p-value]	20.00 [0.000]	44.28 [0.000]

Robust standard errors are in parentheses

$*p<0.1$; $**p<0.05$; $***p<0.01$

Eq. (5) by disentangling the technology adoption dummy variable with respect to, first, the three "technology groups" and, second, the individual technologies. In both cases, non-adopters are considered as the reference category when estimating these modified versions of Eq. (5).

As shown in specification (1) in Table 3, we find that all "technology groups" contribute explaining the labor productivity premium previously estimated for adopters compared to non-adopters. However, production technologies seem to matter the most, followed by customization technologies and, then, by data processing technologies. The results reported in specification (2) refer to individual technologies: we find that only robotics (among production technologies), laser cutting (among customization technologies), and big data and cloud (among data processing technologies) are positively associated with firms'

[10] We report the distribution of adopters by individual technology in Supplementary Table S13.

[11] Supplementary Table S14 reports the results of the factor analysis used to cluster individual technologies.

labor productivity. These findings align partially with existing evidence: previous works have emphasized positive firm-level productivity returns of robotics (Acemoglu et al., 2020; Graetz & Michaels, 2018; Jungmittag & Pesole, 2019; Kromann et al., 2020), as well as that cloud technology plays a significant role in enhancing firms' performance in terms of growth and export capabilities (Boccia et al., 2022; DeStefano et al., 2020). By contrast, there is limited evidence on the role of laser cutting technology for firms' labor productivity: we posit that the importance of this technology is linked to the characteristics of our sample, which consists of MSMEs located in Italy and specialized in industries involving low and medium technologies.

Second, we study the number and variety of technologies adopted. In fact, up to now, we have focused on whether and to what extent the adoption of a new technology influences firms' labor productivity. However, technology adoption is not limited to a single new technology, as firms can decide to adopt one or more new technologies after the first adoption has occurred. On the one hand, 45.6% of adopters has introduced more than one technology, and most of them have introduced two technologies (Supplementary Table S15). On the other hand, only 8.9% of adopters has introduced at least one technology belonging to all the three different "technology groups" in the production process; by contrast, 20.3% of adopters has introduced only production technologies, 34.2% only customization technologies, and 19.0% only data processing technologies in the production process (Supplementary Table S16).

We investigate the labor productivity effects related to the cumulative number of technologies through a variable counting how many technologies a firm has adopted over time, while we investigate the role of variety through a variable counting the number of "technology groups" adopted over time. The first variable ranges in the interval $[0, 7]$, while the second variable ranges in the interval $[0, 3]$. In both cases, non-adopters are considered as the reference category when estimating these modified versions of Eq. (5). These two exercises allow us evaluating also potential non-linearities associated with the number and variety of technologies adopted, under the rationale that a firm requires specific capabilities to manage new technologies in order to achieve an increase in labor productivity (Bloom et al., 2012).

Table 4 reports the results of these exercises. Looking at specification (1), we find an inverted U-shaped relationship between the number of technologies adopted and labor productivity. This result suggests that an excessive number of new technologies could hamper firms' labor productivity, for example, if a firm does not possess internally (or is not able to acquire externally) the resources (e.g., in terms of management and specialized workers) necessary to combine and integrate "harmoniously" the different technological advancements introduced in the production process, and these may increase costs. In particular, we estimate a peak at two technologies, and the labor productivity returns of technology adoption become negative for firms adopting six or more technologies. Specification (2) reports the results concerning the variety of "technology groups." Similar to the previous case, we find an inverted U-shaped relationship between variety and labor productivity. The results suggest that firms adopting technologies belonging to two different "technology groups" benefit the most; by contrast, we do not find evidence of statistically significant effects related to the adoption of technologies belonging to three different "technology groups." These results suggest that firms adopting different technologies may benefit from the fit between technologies and the domain of business applications. Moreover, adopters can also exploit the synergies that integrated Industry 4.0 technologies may offer once adoption includes a variety of technologies with different characteristics. However, excessive variety may be detrimental or, at least, may nullify the positive labor productivity effects of technology adoption.

5 Testing the underlying mechanisms

Our results suggest that firms adopting Industry 4.0 technologies tend to enjoy a labor productivity premium compared to their non-adopting counterparts. We now provide more suggestive evidence on the mechanisms underlying the positive returns of technology adoption on firm labor productivity.

As discussed in Sub-section 2.1, we can identify three main mechanisms explaining the estimated positive productivity returns of technology adoption, namely: efficiency increases in the production process; creation of new knowledge improving the production process and the products; and both greater

Table 4 Number of adopted technologies and variety of adopted technology groups

Dependent variable	$\log(\mathrm{LP}_{ijrt})$	
Estimation method	FE	
Empirical test	Number of technologies	Variety of technology groups
	(1)	(2)
One technology$_{ijrt}$	0.071* (0.041)	…
Two technologies$_{ijrt}$	0.168*** (0.052)	…
Three technologies$_{ijrt}$	0.135* (0.076)	…
Four technologies$_{ijrt}$	0.120** (0.053)	…
Six technologies$_{ijrt}$	−0.183*** (0.054)	…
Seven technologies$_{ijrt}$	−0.239*** (0.069)	…
One technology group$_{ijrt}$	…	0.061* (0.031)
Two technology groups$_{ijrt}$	…	0.107** (0.051)
Three technology groups$_{ijrt}$	…	0.012 (0.052)
Control variables	Yes	Yes
Industry × time trend	Yes	Yes
Region × time trend	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
No. of observations	6460	6460
No. of firms	907	907
R^2	0.705	0.801
Adjusted R^2	0.650	0.765
F statistics [p-value]	10.37 [0.000]	88.51 [0.000]

Robust standard errors are in parentheses

*$p<0.1$; **$p<0.05$; ***$p<0.01$

integration among the internal functions of the firm and greater collaboration with suppliers. We explore these three mechanisms and assess what efficiency dimensions have been affected the most by Industry 4.0 technology adoption by relying on qualitative survey information available for 63 (out of the 79) adopters included in the estimation sample. We have tested the first mechanism on efficiency increases in the production process through information on whether Industry 4.0 technology adoption has determined: a reduction of production costs; a reduction of waste in the production process; and a reduction of the quantity of inputs used in the production process. We have tested the second mechanism on new knowledge creation for production through information on whether Industry 4.0 technology adoption has favored: the creation of new knowledge improving the production process; and the creation of new knowledge improving the products. Finally, we have tested the third mechanism on internal functional integration and external collaboration through information on whether Industry 4.0 technology adoption has led to greater integration among the functions of the firm and greater collaboration between the firm's production function and its suppliers.

We have thus performed a series of one-sample statistical tests to assess whether Industry 4.0 adopters who experienced such gains from technology adoption were a statistically significantly higher percentage than those who did not.[12] The results of this exercise are reported in Table 5: we find support for all the three proposed mechanisms. Indeed, Industry 4.0 technology adoption seems to have increased

[12] Similar to the analysis regarding the difficulties experienced by firms in adopting new technologies, we have tested the true distribution of adopters that gained from technology adoption and those who did not against a hypothetical 50% distribution.

Table 5 Mechanisms underlying technology adoption-driven labor productivity increases

	Yes (%)	Yes (%) > 50% (*p*-value)
Mechanism #1: Industry 4.0 technology increases production efficiency		
Reduction of production costs	64.86	0.035
Reduction of waste in the production process	93.65	0.000
Reduction of the quantity of inputs used in the production process	92.06	0.000
Mechanism #2: Industry 4.0 technology contributes to create new knowledge for production		
New knowledge has been created to improve the production process	95.24	0.000
New knowledge has been created to improve the products	85.71	0.000
Mechanism #3: Industry 4.0 technology leads to greater integration among internal functions and collaboration with suppliers		
Greater integration among functions within the firm	85.71	0.000
Greater collaboration between the production function and the suppliers	85.71	0.000

Percentage values and statistical testing are based on 63 (out of 79) adopters for which survey information is available

efficiency in the production process, favored new knowledge creation for production, and led to both greater functional integration within the firm boundaries and to greater collaboration between the firm and its suppliers. These findings provide both confirmation and novelty in relation to the existing literature on Industry 4.0. They validate the presence of three mechanisms, identified in previous studies, that have the potential to enhance firms' productivity. The novelty lies in the simultaneous presence of all the three mechanisms, indicating a potential systemic impact of Industry 4.0 on labor productivity that extends beyond the boundaries of technology adoption within individual firms.

6 Conclusions

The role new technologies can play in shaping productivity has been the object of great scrutiny. However, empirical research has traditionally adopted an industry-level perspective, and the relatively few micro-level studies have mostly focused on large firms and evaluated the productivity returns of robotics. In this paper, we have explicitly focused on these limitations by analyzing empirically whether and to what extent new technology adoption affects the labor productivity of MSMEs. We have considered a multiplicity of Industry 4.0 technologies and accounted for both additive and variety effects related to technology adoption. Moreover, we have investigated the potential channels driving the labor productivity returns of technology adoption and the role of time in the adoption process.

Our results contribute in improving our understanding of the impacts on firms of the emerging economic paradigm connected to the fourth industrial revolution driven by Industry 4.0, particularly taking into consideration the role MSMEs play in the economy of many advanced countries (Owalla et al., 2022) and the emphasis policymakers are putting through dedicated policy interventions on such a bulk of technologies for fostering firm performance and competitiveness (Brodny & Tutak, 2022).

We have found that the adoption of Industry 4.0 technologies increases adopters' labor productivity by about 7.4%, on average, compared to non-adopters. Our results are in line with previous literature focused on robotics (Acemoglu et al., 2020; Graetz & Michaels, 2018; Jungmittag & Pesole, 2019; Kromann et al., 2020) but also add new evidence as we show that the labor productivity returns of technology adoption are not limited to robotics; rather, they are spread among several Industry 4.0-type technologies (i.e., robotics, laser cutting, and big data and cloud). Moreover, our results are line with more recent contributions on the impact of Industry 4.0 on the performance of small and medium firms (Cirillo et al., 2023; Hwang & Kim, 2022). However, the novelty of our study lies in our ability to both identify the Industry 4.0 technologies adopted by firms and determine the year of their initial adoption. This distinguishes our study from others (e.g., Cirillo et al. (2023)), which have examined adoption within a specific time frame without differentiating whether the adoption represents a first-time occurrence. The inclusion of information regarding the year of first adoption of a new technology enables us to estimate the impact of Industry 4.0 technology on labor productivity over time more accurately.

Another important result of our work is that technology adoption has a sort of "shocking effect" on labor productivity: in fact, its positive returns seem to vanish after 2 years a new technology has been adopted. A possible explanation of this vanishing effect can be attributed to the underestimated "hidden costs" associated with the adoption of new technologies, which MSMEs often discover only after implementation. The limited expertise and managerial skills in handling the integration of these new technologies may cause MSMEs to overlook expenses associated with incorporating the technology within the firm and maintaining it over time.

In addition, our results suggest that adoption has a non-linear effect on labor productivity: indeed, we find evidence of an inverted U-shaped relationship between the number of technologies adopted and productivity, as well as when considering the variety of "technology groups." In this respect, our results corroborate previous research showing diminishing returns of technology adoption (Shephard, 1970). Our explanation is that fiscal incentives supporting the adoption of Industry 4.0 technologies could push firms to adopt more technologies than needed. As a consequence, firms may find it difficult to make the most from newly adopted technologies due to a lack of internal competences necessary to integrate them within the existing production structure. Thus, appropriateness seems to be more important than adoption per se (McAfee, 2004), such that firms that are improving their labor productivity are those that are carefully selecting their "best-fit" technologies among the large portfolio of Industry 4.0 technologies.

Overall, our analysis offers a threefold contribution to the existing literature on technology and labor productivity. First, we contribute to the measurement of the effect of Industry 4.0 on labor productivity by providing novel evidence based on a multiplicity of technologies, besides robotics (Acemoglu et al., 2020; Graetz & Michaels, 2018; Jungmittag & Pesole, 2019; Kromann et al., 2020). Second, we contribute to the scarce existing evidence on MSMEs, which has evaluated almost exclusively the role of ICT on labor productivity (Díaz-Chao et al., 2015), by analyzing the bulk of Industry 4.0 technologies. Our results highlight the high potential Industry 4.0 technologies may have for MSMEs. In this respect, the fact that only a fraction of MSMEs has adopted new available technologies represents a further signal of a "productivity issue" characterizing Italy and the whole European economic system (Rodríguez-Pose & Ganau, 2022). Third, we disentangle the effects of Industry 4.0 on labor productivity by analyzing both additive and variety technology adoption effects.

Our analysis has relevant implications for both practitioners and policymakers. Indeed, our findings clearly suggest that MSMEs can gain in terms of labor productivity—and, consequently, competitiveness—by investing in new technologies. It follows that additional efforts should be put in place by policymakers to design and implement industrial policies promoting the adoption of Industry 4.0 technologies by MSMEs, and this seems to be particularly the case for all those countries—such as Italy—where MSMEs make the bulk of the national industrial system. Furthermore, our findings suggest that practitioners and policymakers should also consider the relative decline in productivity observed 2 years after the introduction of Industry 4.0 technologies. We believe that, in addition to promoting the adoption of these technologies, it is crucial to prioritize the overall quality of firms' implementation strategies. This approach is necessary to effectively address the hidden costs associated with the technology and ensure successful outcomes.

We acknowledge that our research has some limitations. First, the wealth of survey information comes at the cost of a relatively small number of firms disclosing detailed information on Industry 4.0 adoption paths. Second, future research could expand the analysis internationally taking into consideration the different structural presence of MSMEs across countries. Third, data availability constraints prevented us from accounting for the role firm-specific digital capabilities can have in moderating the returns of technology adoption on labor productivity. Future research could enlarge our study by including also the perspective of internal competences and MSMEs' resource endowment on productivity.

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