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Abstract

Do new manufacturing technologies of the Industry 4.0 (I4.0) boost TFP growth? By adopting a distance-to-frontier framework, this paper explores whether the adoption of (advanced) digital technologies affect the sectoral TFP growth rates across manufacturing industries of 14 European countries, during the period 2009–2019. We rely on a novel measure of adoption of I4.0 technologies (namely, advanced industrial robots, additive manufacturing and industrial internet of things), exploiting highly detailed (8-digit level) information on imports of capital goods embodying such technologies. Our results suggest that adopting new digital manufacturing technologies of the I4.0 brings quantitatively important and statistically significant contributions to sectoral TFP growth rates, although these are mostly concentrated in countries close to the technology frontier. In turn, these technologies seem to have hampered the process of convergence between European technological leaders and laggards over the last decade.

Keywords: Industry 4.0; fourth industrial revolution; technology diffusion; total factor productivity (TFP); technological convergence.

JEL classification: O11; O33; O47.

1. Introduction

Over the last decade, academics, policymakers, and practitioners ranging from engineers to managers and entrepreneurs have looked at technological changes in production processes – embodied by the advent of new digital and '*smart*' technologies – with a growing interest (Brynjolfsson and McAfee, 2014). The fourth industrial revolution (4IR), also known as '*Industry 4.0*' (I4.0) in manufacturing (Skilton and Hovsepian, 2017), is leading to new digital paradigms driven by the diffusion of a vast array of automation technologies.

The combination of robots, additive manufacturing (or 3D printing), the internet of things, big data, artificial intelligence, and other new digital technologies enables the creation of cyber-physical systems which integrate seamlessly physical operations with digital insight (Davies, 2015; Eurofound, 2018; Kagermann et al., 2013; Mariani and Borghi, 2019), enabling the creation of smart factories (Wang et al., 2016).

Overall, digital manufacturing and automation technologies of the 4IR can provide firms with new capabilities to perform flexibly, collaboratively and resiliently (Dalenogare et al., 2018; Frank et al., 2019; Marcucci et al., 2021), leading to higher cost-efficiency and productivity (Kagermann et al., 2013; Müller, Buliga and Voigt, 2018) while also benefitting the market competition and contribute to overall economic and productivity growth, particularly in more developed economies.

As such, the growing diffusion of I4.0 technologies may offer the opportunity to revert the downward trend in productivity growth (Mokyr, 2018; Pompei and Venturini, 2022) and the process of divergence between more productive (frontier) and laggard firms (Andrews et al., 2019).

Despite the attention given to the 4IR by academics and institutional actors, the empirical evidence concerning these phenomena is still limited, along with suitable measures of I4.0 technology adoption enabling the investigation of their effects across countries, industries and over time. In particular, the 4IR-productivity nexus has attracted an increasing amount of research in the last few years. However, most empirical contributions focus on the adoption of specific technologies, mainly industrial robots (Cette et al., 2021; Du and Lin, 2022; Graetz and Michaels, 2018) or look at a single country (Acemoglu et al., 2020; Ballestar et al., 2020; Bonfiglioli et al., 2020). Other works provide only descriptive evidence on the adoption pattern across countries (e.g., Foster-McGregor et al., 2019), while most studies focusing on technologies of the 4IR primarily investigate the impact of adoption on occupation and jobs (e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021).

We take stock of this growing literature and move it forward by exploring the role played by a larger set of technologies in generating productivity growth and convergence, using a panel of 13 manufacturing industries across 14 European countries over the 2009–2019 period. Specifically, we focus on three '*physical*' advanced manufacturing technologies of the I4.0 technologies – namely, advanced industrial robots (AIRs), additive manufacturing (AM) and industrial internet of things (IIoT) – considered as potentially '*game-changing*' (i.e., disrupting) in manufacturing (Eurofound, 2018, p. 3),[1] and we test whether their adoption triggers additional productivity gains, potentially facilitating the catching-up of countries and sectors more distant from the frontier or further deepening the technological gap between more developed and laggard economies across Europe.

Beyond consistent physical and monetary investments, they also require a certain level of absorptive capacity, prior investments in enabling technologies to be effectively adopted. In turn, the presence of such barriers to an effective adoption of these technologies may slow down or even '*disable*' the process of technological convergence. This motivates our interest towards the

[1] Their disruptive potential results from their potential for a widespread application across every manufacturing industry due to their "*versatility and complementarity"* (Eurofound, 2018, p. 3). Furthermore, while we already acknowledged the impact I4.0 technologies have on manufacturing operations – e.g., higher operational flexibility, higher production efficiency and quality, lower set-up costs and integration along the value chain, resulting in higher productivity and better performance overall (see also Skilton and Hovsepian, 2017; Eurofound, 2018) – additional high-level impact resides in the world of work and, in general, the entire society. On the one hand, a general concern around the "*risks of new monopolies, mass redundancies, spying on workers, and the extension of precarious digital work*" (Davies, 2015, p. 9) emerges. On the other hand, this transformation calls for a policy debate on the upcoming changes in the task content and occupational profiles of manufacturing employment (Frey and Osborne, 2017; Eurofound, 2018).

existence of potentially different effects across countries and industries, depending on the relative distance to the technology frontier.

Guided by these premises, the present study investigates the productivity effects associated with the adoption of I4.0 technologies by looking at: (i) their effects on total factor productivity (TFP) growth; (ii) the potential heterogenous effect across different technologies; and (iii) their potential role of enablers of productivity catch-up (convergence) across manufacturing industries of European economies. We follow a robust empirical approach, that is the distance-to-frontier (DTF) framework, widely used in previous works looking at different levels of aggregation (Andrews et al., 2019; Cameron et al., 2005; Griffith et al., 2004; Griffith et al., 2009; Mason et al., 2020; Minniti and Venturini, 2017; Pompei and Venturini, 2022).

The empirical analysis exploits a panel of 13 manufacturing industries across 14 European countries over the 2009–2019 period. We measure I4.0 technology adoption by using import data for highly disaggregated (8-digit) product categories related to AIRs, AM and IIoT since they are embodied technologies, requiring the physical installation of specialised capital goods (Domini et al. 2021). Our results highlight that I4.0 technologies brought relevant contributions to TFP growth rates over the last decade. Looking at individual technologies, we find that AM and AIRs are the most beneficial (on average) for European economies across manufacturing industries, while the effect of IIoT on TFP growth is weaker and mostly confined to more developed economies. At the same time, we find that productivity gains from I4.0 technology adoption mostly concentrate in countries closer to the technology frontier, thus suggesting that (on aggregate) these technologies are not currently helping productivity convergence.

We contribute to the literature in two main ways: first, we address the debate on global productivity slowdown and secular stagnation by analysing the effect that adopting new technologies of the 4IR may have on reverting such trends. While our results indicate that the diffusion of I4.0 technologies may indeed result in sustained TFP growth in the long-run, so far this has been happening at a different pace across European countries, thus hindering convergence. This evidence provides support to the recent discussion on these technologies' requirements in terms of absorptive capacity and investments in enabling technologies (Ciffolilli and Muscio, 2018; Corradini et al., 2021). Second, from a methodological and empirical standpoint, our work is one of the first to use highly detailed import data for several I4.0 technologies and across countries to measure sectoral adoption. As compared to other data sources (e.g., surveys, data on IT staff/AI expert hirings/expenditure), our approach is scalable over time and across countries, and provides comparable estimates across different technologies. Additionally, while the focus of this paper is at a national and sectoral level, trade data is increasingly available at the establishment level, thus allowing to adopt our proposed methodology at this much granular level of analysis. Indeed, several statistical offices are allowing researchers to access detailed import and export data at the transaction level.

The rest of the paper is structured as follows. Section 2 discusses the relevant literature on the topic, Section 3 highlights the analytical framework and the empirical strategy for our empirical investigation. Section 4 discusses the data used, while Section 5 presents and discusses the results of our econometric analysis and the related robustness tests. Finally, Section 6 discusses results, the related policy implications, and concludes by discussing limitations and outlining future research.

2. Background literature

The 4IR and its technologies have been at the core of academics' debate for over a decade now. From a conceptual standpoint, these technologies represent a new and more advanced form of capital. By substituting or complementing traditional types of automated machinery, I4.0 technologies can perform a growing number of tasks in a faster and more efficient way, in turn, rising productivity, but also generating new ideas and boosting innovation.

In the smart factory, latest improvements in dynamic programming paired with the use of smart sensors enable advanced industrial robots (AIRs) to perform a broader range of tasks as compared to their predecessors, offering accuracy, flexibility, and both collaborative (human-machine) and autonomous applications (Davies, 2015; Eurofound, 2018; Frey and Osborne, 2017). At the same time, additive manufacturing (AM) provides firms with the possibility to expand their product range, for instance by creating new niche markets, offers new opportunities for real-time customization, enabling to speed up the entire product development cycle, and paves the way to innovative business models (Bogers et al., 2016; Rayna and Striukova, 2016), while also reducing the number of production stages, production (e.g., material consumption) and logistic costs, and overall operational complexity (Felice et al., 2022; Weller et al., 2015). Furthermore, the extensive adoption of sensors, actuators and distributed systems (e.g., NFC microchips, RFID tags and GPS) enables the creation of industrial internet of things (IIoT) environments (Atzori et al., 2010) which provide high communication and integration potential, eventually empowering a more efficient management of industrial operations and digital integration between firms operating along the value chain (Wang et al., 2016). This infrastructure allows to pull together a variety of data from interconnected devices (e.g., efficiency, machine usage, energy consumption), which are used to increase reliability of productive assets and for predictive maintenance, to automate and optimise production, minimise costs and improve output quality, but also to increase communication and coordination along the supply chain (Dalenogare et al., 2018; Frank et al., 2019; Marcucci et al., 2021; Müller, Buliga and Voigt, 2018), ultimately increasing productivity.

However, given the lack of extensive and detailed sources of information on the adoption of I4.0 technologies (Brynjolfsson et al., 2019; Cockburn et al., 2019), most of the studies in the field have focused on AIRs thanks to data from the International Federation of Robotics (IFR), mostly looking at the occupational and wage effects of robotisation at different level of analysis (e.g., Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021).

Recently, a growing body of works has looked at the productivity effects (both labour productivity and TFP) deriving from the adoption of specific '*physical*' automation or I4.0-related technologies.[2] Using the growth accounting approach and looking at 30 OECD countries, Cette et al. (2021) find that aggregate AIR adoption does not appear to have been a quantitatively significant source of productivity growth between 1975 and 2019. Similarly, also Edquist et al. (2019) and Espinoza et al. (2020) leverage on growth accounting to investigate productivity gains associated with the adoption of IoT. The former authors use data on licensed IoT connections across 82 countries for the period 2010–2017 finding that a 10% increase in the growth rate of IoT connections per inhabitant is associated with a 0.23% increase in economy-wide TFP growth. Espinoza et al. (2020) combine earlier findings on the contribution of ICT to (labour) productivity growth with new cross-country data on IoT expenditure, estimating the share of ICT-related productivity gains coming from IoT investments to be about 0.01 percentage points (pp) in the US and 0.006 pp across EU10 countries.

Looking at industry-level growth, Graetz and Michaels (2018) estimate that the rising adoption of AIRs can explain from 0.4 to 1% of the increase in labour productivity and from 0.3 to 0.8% of TFP growth between 1993 and 2007, in a sample of 17 OECD economies. Similarly, Du and Lin (2022) exploit sectoral data on AIR adoption to measure robotisation rates across Chinese regions – following the empirical approach by Acemoglu and Restrepo (2020) – and uncover a U-shaped relationship with TFP growth for which productivity gains are mostly located in regions showing high robotisation.

At the firm level, Jäger et al. (2015) find significant higher labour productivity gains associated with AIR adoption in manufacturing operations by looking at around 1,400 Swiss and Dutch businesses. Similarly, Ballestar et al. (2020) analyse a sample of Spanish firms between 2008

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[2] In this work, we focus on studies addressing the implications of 'physical' I4.0 technology adoption. We stress the difference between 'physical' (i.e., capital embodied) and 'digital' (i.e., software-related) I4.0 technologies as such characteristic represents a crucial distinction, as also observed by Foster-McGregor et al. (2019). In so doing, we intentionally avoid a detailed review of studies addressing the productivity implication of I4.0 technology development and innovation (e.g., patenting artificial intelligence; for a recent contribution, see Venturini, 2022) as this would fall outside the purpose of our research. Notwithstanding, we redirect the reader to recent studies from Czarnitzki et al. (2023) and Müller, Fay and Brocke (2018) who explore the productivity effects of 'digital' I4.0 technology adoption, i.e. artificial intelligence and big data, respectively.

and 2015, uncovering a rise in productivity of about 3% across small and medium sized firms (SMEs) associated with AIR adoption, but no effect on large companies. Acemoglu et al. (2020) and Bonfiglioli et al. (2020) look at AIR adoption across French firms, although uncovering mixed findings: while the former authors find unconclusive and not robust evidence on the impact of AIR adoption on TFP growth between 2010 and 2015, the latter find a positive and significant effect over a longer period from 1994 to 2013, robust to several checks.

Although previous studies have moved the debate forward, they bear some limitations. First, they measure the adoption of single technologies (mostly AIR and, in some cases, IoT) and neglect the implications coming from a wider and more complete nexus of technologies. Second, they focus on different levels of aggregation (country vs sector vs firm level) and on different periods, thus making it hard to compare insights. Furthermore, while providing interesting insights, these works base their analysis on different and only partially comparable measures for the same technology: e.g. IFR data in Graetz and Michaels (2018), Cette et al. (2021) and Du and Lin (2022), AIR adoption dummy in Ballestar et al. (2020), and AIR imports in Acemoglu et al. (2020) and Bonfiglioli et al. (2020). Finally, some of these works bear important limitations from an empirical standpoint: on the one hand, cross-sectional data (Ballestar et al., 2020; Jäger et al., 2015) or too short time series (Edquist et al., 2019) do not allow to investigate causal relationships; on the other hand, studies performing sensitivity analyses do not enable to produce accurate estimates (Espinoza et al., 2020).

This study addresses these limitations by providing a unified measurement framework for different I4.0 technologies, testing their effect on productivity growth of 14 European countries and 13 manufacturing industries over a decade (2009–2019). We employ a panel data econometric model which assumes that in each industry there is a stable, long-run, relationship between TFP levels of frontier and laggard countries.

All the above discussion conceptualises, with empirical support, a direct effect of I4.0 technologies and productivity. However, the effect of the adoption could generate catching-up mechanisms helping lagging countries to reduce their distance to the technological frontier. Following this line, some recent studies looking at innovation activities of I4.0 related technologies have found a catching-up effect, where companies introducing I4.0 patents enjoy significantly higher TFP growth, proportional to their distance from frontier firms (Pompei and Venturini, 2022). However, I4.0 technologies are characterised by peculiar features and embody some of the most recent forms of technological change, hence they could require both absorptive capacity and complementarity with existing enabling technologies to be efficiently adopted (Ciffolilli and Muscio, 2018; Corradini et al., 2021).

Thus, while at the aggregate level we expect positive TFP gains from adopting I4.0 technologies, their effect might be larger and concentrated in more developed economies and not consistently beneficial for technological laggards. Moreover, we expect differential patterns and magnitudes when distinguishing between I4.0 technologies, since some countries might have easier access – in terms of capital requirements – and higher capabilities to use and exploit some technologies (e.g., additive manufacturing) rather than others (e.g., industrial internet of things), due to their peculiar characteristics.

3. Empirical setting

In line with our conceptualisation, our analysis of the sectoral productivity effects of I4.0 technologies is based on the distance-to-frontier (DTF) framework (Bernard and Jones, 1996), which assumes that, in each industry, there is a stable, long-run, relationship between TFP levels of frontier (F) and laggard countries (i). In laggard countries i, TFP in sector j can grow as a result of technological improvements at the frontier F and technology transfer from the frontier. TFP (A) is allowed to vary across countries, industries and time and is derived from the following production function:

$$Y_{ijt} = A_{ijt}G_{ij}(X_{ijt}, L_{ijt}, K_{ijt}) \qquad (1)$$

where Y denotes gross output produced in each country using intermediate inputs X, labour L and capital K inputs; function $G(\cdot,\cdot)$ is assumed to be homogeneous of degree one and to exhibit diminishing marginal returns to the accumulation of each individual production factor and constant returns to scale. The model also allows any country to switch endogenously from being a frontier to a non-frontier country and vice versa, in a way that in steady state the frontier for sector j will be whichever country featuring the highest TFP level in that sector. Each non-frontier country i will be at an equilibrium distance behind the leader F such that all countries feature the same TFP growth rate.

Under the standard assumptions discussed above, the relationship between the TFP level of laggard countries and the TFP level at the frontier can be formalised as an equilibrium correction model (ECM) representation, featuring a first-order autoregressive distributed lag model (ADL(1,1)) which assumes a long-run cointegrating relationship between a country's own TFP and technological leader's TFP:

$$lnA_{ijt} = \lambda_1 lnA_{ijt-1} + \lambda_2 lnA_{Fjt} + \lambda_3 lnA_{Fjt-1} + u_{ijt}. \tag{2}$$

where lnA_{ijt} denotes TFP level of laggard countries and lnA_{Fjt} denotes TFP level of the frontier, in each sector j. Assuming long-run homogeneity ($\lambda_1 + \lambda_2 + \lambda_3 = 1$), Eq. (2) can be expressed as:

$$\Delta lnA_{ijt} = \lambda_2 \Delta lnA_{Fjt} + (1 - \lambda_1) \underbrace{ln\left(\frac{A_F}{A_i}\right)_{jt-1}}_{lnDTF_{ijt-1}} + u_{ijt} \tag{3}$$

where the term $ln(A_F/A_i)_{jt-1}$ (i.e., $lnDTF_{ijt-1}$) represents the distance-to-frontier expressed as a function of the lagged productivity differentials in sector j between country i and country F, capturing the potential for country i's productivity growth from catching-up. The rationale for Eq. (3) is that, for a non-frontier country i the potential for catching-up to the leader ($lnDTF_{ijt-1}$) is positive and larger the further away country i lies from the frontier in sector j, rising the potential for productivity gains. In the case of the frontier instead, the sole source of productivity growth resides in domestic innovation, such that the second term in the right-hand side of Eq. (3) is null.

Following the literature on endogenous growth we recognise the role variables such as R&D, international trade and ICTs have in determining productivity growth. At the same time, following the convergence literature, we assume these variables can affect TFP growth through both domestic innovation and technology transfer. In addition to these traditional determinants of TFP growth, here we augment the model with variables measuring the adoption of I4.0 technologies. Our final econometric specification becomes:

$$\begin{aligned}\Delta lnA_{ijt} = \alpha_1 \Delta lnA_{Fjt} + \alpha_2 lnDTF_{ijt-1} + \alpha_3 I40_{ijt-1} + \alpha_4 I40_{ijt-1} \times lnDTF_{ijt-1} \\ + \alpha_5 X_{ijt-1} + \alpha_6 X_{ijt-1} \times lnDTF_{ijt-1} + \eta_{ij} + \tau_t + \varepsilon_{ijt}\end{aligned} \quad (4)$$

where ΔlnA_{ijt}, ΔlnA_{Fjt} and $lnDTF_{ijt-1}$ are defined as above, $I40_{ijt-1}$ is our main explanatory variable capturing the stock of investments in the three I4.0 technologies (i.e., AIRs, AM and IIoT) at the country-sector level and X_{ijt-1} is a vector of control variables. A positive value for α_2 implies that technology transfer is relevant for technological laggards, thus translating in productivity catch-up. If I4.0 technology adoption spurs productivity gains, α_3 should be positive; at the same time, if it brings greater TFP growth for countries closer to (farther away from) the frontier α_4 should be negative (positive).

As described in Castellani et al. (2022), the 4IR technologies investigated here show a distinct pattern of diffusion across Europe. Following the discussion in Section 2, we expect positive TFP gains from I4.0 technologies adoption (i.e., a positive α_3), while it is likely that their effect will be very limited for technological laggard. Hence, we expect a negative α_4.

Eq. (4) includes unobserved heterogeneity arising from country-industry characteristics not captured by our explanatory variables, affecting rates of TFP growth, and possibly correlated with our controls. For instance, there may be some specific characteristics related to the production technology in specific countries and sectors that might push TFP to grow faster in exactly those country-sector pairs showing higher intensities in investments in I4.0 technologies, R&D or trade patterns. For this reason, our identification strategy is based on the within-groups estimator, i.e. we include country-sector fixed effects (η_{ij}, hereafter FE). We further include time FE (τ_t) to capture the potential component of technical change, evolving over time, which is common to all countries and sectors, as well as common macroeconomic trends and shocks. Since heteroskedasticity is pervasive in our industry-level data, and hypotheses tests on our sectoral variables indicates that variances are heterogeneous across country-sector groups, we estimate all specifications of Eq. (4) by Weighted Least Squares (WLS) using value added shares in total economy as weights. In Section 5.3, we discuss the robustness of our results to potential endogeneity concerns by providing several econometric checks, and we test the robustness of our main results to a range of alternative specifications.

4. Data

4.1. TFP growth and levels

To compute our dependent variable, TFP growth rate, we use sectoral data on gross output, value added, labour, total capital stock and intermediate inputs for European countries, the US and Japan from the 2021 release of EU KLEMS database (February 2022 revision). We complement EU KLEMS data with comparable information from OECD STAN data set.

We adopt the superlative index approach first introduced by Caves et al. (1982). The approach assumes that the underlying production function is translog and is widely used in cross-country analysis at various levels of aggregation (Cameron et al., 2005; Griffith et al., 2004; Griffith et al., 2009; Mason et al., 2020; Pompei and Venturini, 2022; Venturini, 2015). Following Jorgenson et al. (2005), we compute TFP growth rates as:

$$\Delta lnA_{ijt} = \Delta lnY_{ijt} - \breve{v}_{ijt}^{X}\Delta lnX_{ijt} - \breve{v}_{ijt}^{K}\Delta lnK_{ijt} - \breve{v}_{ijt}^{L}\Delta lnL_{ijt} \quad (5)$$

where $\breve{v}_{ilt}^{X}$, $\breve{v}_{ilt}^{K}$ and $\breve{v}_{ilt}^{L}$ represent the share of nominal intermediate inputs, the share of capital compensation and the share of labour compensation in gross output, respectively. Terms $\breve{v}_{ijt}$

represent the '*divisia index*' and are computed as $\breve{v}_{ijt} = 0.5(v_{ijt} + v_{ijt-1})$. Assuming constant returns to scale implies that $\breve{v}_{ijt}^{X} + \breve{v}_{ijt}^{K} + \breve{v}_{ijt}^{L} = 1$.

We measure TFP levels using the same approach, evaluating TFP relative to a common reference point (i.e., the geometric mean of the TFP levels of all other countries):

$$\text{ln}A_{ijt} = ln\left(\frac{Y_i}{\overline{Y}}\right)_{jt} - \tilde{v}_{ijt}^{X} ln\left(\frac{X_i}{\overline{X}}\right)_{jt} - \tilde{v}_{ijt}^{K} ln\left(\frac{K_i}{\overline{K}}\right)_{jt} - \tilde{v}_{ijt}^{L} ln\left(\frac{L_i}{\overline{L}}\right)_{jt} \tag{6}$$

where $\overline{Y}$, $\overline{X}$, $\overline{K}$ and $\overline{L}$ denote the country-level geometric means of gross output, intermediate inputs, aggregate capital stock and labour, and $\tilde{v}_{ijt} = 0.5(v_{ijt} + \bar{v}_{ijt})$ are the averages of nominal input cost shares and their geometric means. In each time t and sector j, we take the country with the highest TFP level as the frontier, so that $lnDTF_{ijt}$ is computed as the difference between lnA_{Fjt} and lnA_{ijt}.

In order to better specify our econometric model using the DTF framework, although we look at European countries, we also use data on the US and Japan to compute TFP levels and growth rates to expand the range of more developed economies possibly featuring as the frontier.

We also deal with measurement issues related to differences across countries in hours worked and skills levels by computing alternative TFP measures, adjusted for differences in hours worked and skills levels. Appendix A reports details on how we compute these alternative TFP measures.

4.2. Measuring I4.0 technology adoption

To compute our main variables of interest, the adoption of the three I4.0 technologies considered in the study (i.e., AIRs, AM and IIoT), we use country-level highly disaggregated trade data from Eurostat's Comext database, providing fine-grained 8-digit product codes related to such technologies. Comext dataset includes virtually complete information on trade transactions, since intra- and extra-EU trade data are electronically collected through customs when goods transit EU28's borders, granting full coverage.

Product codes reported in Comext data follow the Combined Nomenclature (CN), a more detailed breakdown of the Harmonised System. We followed a structured approach to identify product codes in the CN specifically capturing trade of I4.0 technologies. Details on the methodology followed for the identification and the validation of I4.0-related product codes are reported in Appendix B. We checked for changes occurred in the CN classification between 2009 and 2019 in each year, so to track all potential changes related to the selected codes. Whenever the CN classification changed over time, we followed Van Beveren et al. (2012), creating '*synthetic*' codes grouping together the relevant CN codes. The procedure grants full consistency in the correspondence between trade data over time and has been increasingly used in recent works looking at highly disaggregated trade dynamics (e.g., Castellani and Fassio, 2019; Bontadini and Vona, 2023).

We then computed our measures proxying the adoption of I4.0 as the sum of the import values for all product codes relating to AIRs AM and IIoT, for each country and year of observation. This measure is inspired by Caselli and Coleman (2001) and similar measures of technology adoption have been used in some recent studies (Acemoglu et al., 2020; Acemoglu and Restrepo, 2022; Bonfiglioli et al., 2020; Domini et al., 2021; 2022;). However, these works look at more aggregated (6-digit) product categories, capturing a broader definition of automation technologies and reaching outside the boundaries of the 4IR.

Since sectoral import data at a high level of detail (allowing an accurate identification of I4.0-related products) is not available, we follow the approach used in previous studies (Acemoglu and Restrepo, 2020; Felice et al., 2022; Venturini, 2022), building our sectoral I4.0 measure as import-weighted shares of technology adoption.[3] We exploit: i) the information on each country's

[3] This measure is similar to the robot exposure index proposed by Acemoglu and Restrepo (2020) to measure robot adoption at the local labour market level, used in several empirical studies, and to the import-weighted measures of I4.0 technology production proposed by Felice et al. (2022) and Venturini (2022).

share of imported I4.0-related goods over total imports from I4.0-producing sectors;[4] ii) cross-country and cross-sector data on imported intermediate inputs from WIOD data set (Timmer et al., 2015). In so doing, we assume that each industry adopts I4.0 technologies in the same proportion as it uses I4.0-related inputs from the sector producing each specific technology (i.e., 28 for AIRs and AM, 26 for IIoT):

$$M_{i,j,t}^{I40} = \left(M_{i,t}^{AIR} \times \varphi_i^{AIR} \times \frac{\sum_c int_{i,j}^{c,28}}{\sum_c \sum_s int_{i,j}^{c,s}} \right) + \left(M_{i,t}^{AM} \times \varphi_i^{AM} \times \frac{\sum_c int_{i,j}^{c,28}}{\sum_c \sum_s int_{i,j}^{c,s}} \right) + \left(M_{i,t}^{IIoT} \times \varphi_i^{IIoT} \times \frac{\sum_c int_{i,j}^{c,26}}{\sum_c \sum_s int_{i,j}^{c,s}} \right) \quad (7)$$

where i and j denote the country and the sector buying intermediates (i.e., the destination); c and s denote the country and the sector selling intermediates (i.e., the source); $\varphi_i^{AIR} = M_i^{AIR}/M_i^{28}$ denotes, in each country i, the share of AIR imports in all imports of goods produced by sector 28; $\varphi_i^{AM} = M_i^{AM}/M_i^{28}$ denotes the same share for AM; $\varphi_i^{IIoT} = M_i^{IIoT}/M_i^{26}$ denotes the share of IIoT imports in all imports of goods produced by sector 26. The last term in each parenthesis of Eq. (7) (e.g., $\sum_c int_{i,j}^{c,28}/\sum_c \sum_s int_{i,j}^{c,s}$) represents, for each country i and sector j, the share of intermediates produced by the I4.0-producing sector and imported from any other country in all imported intermediates.

Formally, for each country i, sector j and year t, I4.0 imports (M_{ijt}^{I40}) are equal to the sum of imports of each I4.0 technology in each country, weighted by the ratio of I4.0-related intermediate goods bought by sector j of country i from the sector producing each specific technology (i.e., 28 for AIRs and AM, 26 for IIoT) in all other countries ($c \neq i$) over total intermediate goods used by sector j in country i (int_{ij}). We take predetermined weights (i.e., in 2008) in order to avoid potential reverse causality bias. The idea behind this measure is that true sectoral I4.0 technology

[4] This information is computed by matching the 8-digit CN product codes for I4.0-related capital and intermediate goods with the corresponding 8-digit codes in Prodcom classification. In the Prodcom list, the first 4 digits of each product code coincide with the 4-digit NACE sector producing the good (Eurostat, 2021).

adoption (unfortunately, not available for all technologies, countries and years) should be positively correlated with our measure, i.e. the more a sector buys I4.0-related inputs from I4.0 producing sectors, the larger its level of adoption.

We then compute the stock of sectoral I4.0 imports ($I40_{ijt}$) following the perpetual inventory method as $I40_{ijt} = M_{ijt}^{I40} + (1-\delta)I40_{ijt-1}$, assuming a depreciation rate of 15%. We also test specifications of our model in which we delve into the specific relationship, and related magnitude, of each single I4.0 technology. The related measures for AIRs, AM and IIoT are built following the same methodology.[5] All these measures are included in our models as shares in value added.

4.3. Other independent variables

In addition to country-sector and year fixed-effects, we include controls for R&D and ICT capital stocks as shares of value added. To avoid that our I4.0 adoption variables pick up a general effect from imported goods, we also control for the share of imports in value added. All these variables vary over countries, sectors, and years. We sourced this information from EU KLEMS database, OECD STAN, ANBERD and BTDIxE data sets. When building all our variables, we adjusted current values using specific sectoral deflators from OECD STAN and converting all data in USD.[6]

Our sample consists of 14 European countries[7] and 13 manufacturing industries[8] over the 2009–2019 period. Table 1 below presents summary statistics of all variables, while Table C1 in Appendix C reports a detailed description of all variables and a summary description.

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[5] Data on I4.0 adoption measures (i.e., flows and stocks, aggregate and for each technology) are available upon request.
[6] We do not use sectoral PPPs, which would enable a more precise comparison across countries and sectors, since these are hardly available for all countries, sectors and years in our analysis. However, this is a lesser concern for our work as by using the within-groups estimator we should be able to filter out cross-country and cross-sector differences in prices.
[7] Country list: Austria (AUT), Belgium (BEL), Czech Republic (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), United Kingdom (GBR), Italy (ITA), Netherland (NLD), Portugal (PRT), Slovak Republic (SVK), Sweden (SWE).
[8] Manufacturing industries list (NACE rev.2): 1 - Food products, beverages and tobacco (10-12); 2 - Textiles, wearing apparel, leather and related products (13-15); 3 - Wood and paper products; printing and reproduction of recorded media (16-18); 4 - Coke and refined petroleum products (19); 5 - Chemicals and chemical products (20); 6 - Basic

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Table 1 around here

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5. Results

5.1. Main results

Before presenting our main results, we test the presence of unit roots in the data used for our analysis by employing Im, Pesaran and Shin (2003) test. Table 2 shows that all the variables included in our models are stationary. We further test the long-run cointegrating relationship among the variables included in our model by using the panel cointegration test proposed by Pedroni (2004). The results presented in Table 3 confirm a long-run cointegrating relationship among model variables testing residuals of both Phillips–Perron (PP) and Augmented Dickey–Fuller (ADF) regressions, all significant at the 1% level.

Tables 2 and 3 around here

Table 4 shows our estimates of the model described by Eq. (4). Our starting point is to estimate a benchmark model including only determinants of TFP growth extensively studied in the literature, i.e. R&D, imports and ICT intensity.

We begin in column (1) by estimating the long-run relationship between TFP growth rates and R&D, import and ICT variables between 1995 and 2019. This baseline model provides us with

pharmaceutical products and pharmaceutical preparations (21); 7 - Rubber and plastics products, and other non-metallic mineral products (22-23); 8 - Basic metals and fabricated metal products, except machinery and equipment (24-25); 9 - Computer, electronic and optical products (26); 10 - Electrical equipment (27); 11 - Machinery and equipment n.e.c. (28); 12 - Transport equipment (29-30); 13 - Other manufacturing; repair and installation of machinery and equipment (31-33).

a robust starting point for the analysis, increasing comparability with prior studies. TFP growth of the frontier (ΔlnA_F) and the distance-to-frontier ($lnDTF$) terms are positive and statistically significant at the 1% level. This indicates that, within each manufacturing industry, European countries benefitted from both technological progress at the frontier and from productivity gains associated with catching-up. This result is in line with prior sector-level evidence for developed economies spanning between the 70s and early 2000s (Griffith et al., 2004; Cameron et al., 2005; Mc Morrow et al., 2008; Minniti and Venturini, 2017; Mason et al., 2020), and persistent up to before the Covid-19 pandemic, as shown by our results.

Along with other studies (Griffith et al., 2004; Madsen et al., 2010), we find a positive and statistically significant (at the 1% level) relationship between R&D investments and TFP growth rates, but these gains are concentrated in countries closer to the frontier (i.e., the interaction with the $lnDTF$ term is also statistically significant and negative). Conversely, import intensity seems to feature a negative direct relationship with TFP growth, but at the same time facilitates catching-up (both coefficients are significant at the 5% level), in line with prior works (Griffith et al., 2004). Finally, and similarly to other studies (Bakhshi and Larsen, 2005; Martínez et al., 2010; Venturini, 2015; Bergeaud et al., 2016), our estimates highlight that ICT investments had a positive effect on TFP growth rates (significant at the 5% level), yet mostly concentrated in more developed European economies.

In columns (2) and (3) we then split the sample period, looking at the period 1995–2008 in column (2) and at the period 2009–2019 in column (3). As discussed by Castellani et al. (2022), the year 2009 represents a meaningful starting point for our investigation since: i) only after the 2008 global financial crisis these technologies started receiving increasing attention from European policymakers and the worldwide demand for advanced mechanical and automation equipment returned to normal (Kagermann et al., 2013; De Backer et al., 2018); ii) several core patents protecting AM technologies, such as fused deposition modelling and selective laser sintering, expired between 2009 and 2014 (Felice et al., 2022), leading to a proliferation of spill-over inventions and machinery producers.

From column (2), we note that imports had a no significant effect between 1995 and 2008. Similarly, the effect of ICT investments is estimated less precisely and turns out not significant, pointing at similar results as found in some studies looking at manufacturing industries over the same period (Mc Morrow et al., 2008; Edquist and Henrekson, 2017). Conversely, looking at the 2009–2019 period in column (3), ICT investments appear to have a positive and significant effect on TFP growth rates across manufacturing industries, again concentrated in more developed countries. This finding provides updated evidence of the role of ICTs both as a driver of productivity growth and as a facilitator of catching-up for laggard countries, highlighting that the downward trend observed in previous studies (Bergeaud et al., 2016; Chung, 2018) has partially reversed, especially in the more technologically advanced European countries.[9]

Finally, we introduce our measure of sectoral I4.0 technology adoption alone (column (4)) and allowing it to have an effect on the productivity growth of lagging countries (column (5)). In column (4), the direct effect of adopting I4.0 technologies is estimated with little precision, resulting not statistically different from zero. However, when accounting for the role of I4.0 technologies as facilitators of catching-up ($I40 \times lnDTF$) in column (5), the I4.0 adoption variable increases in magnitude and become statistically significant at the 1% level, while the interaction term enters our specification with a negative and statistically significant (1% level) coefficient. This result suggests that I4.0 technologies bring productivity gains for economies closer to the frontier while countries lagging behind the frontier do not enjoy any additional I4.0-related technological catch-up.

In columns from (6) to (8) we explore additional specifications where TFP measures reflect cross-country differences in the skill composition of the workforce (column (6)), in hours worked

[9] See, for instance, Cardona et al. (2013) and Schweikl and Obermaier (2020) for recent surveys of the literature on ICT and productivity.

and skill composition (column (7)), and account for an alternative definition of the technology frontier[10] (column (8)). Our main results are robust and qualitatively unchanged cross these specifications, confirming a positive effect of adopting I4.0 technologies on productivity growth. Notably, the specifications correcting TFP measurement for hours worked and skills also highlight that accounting for these factors reduces the importance of spill-overs from the leader's growth (i.e., ΔlnA_F's coefficient reduces in magnitude and is no longer significant), while it also uncovers a consistently bigger role of R&D investments (in column (6), RD's coefficient becomes three times bigger than in column (5), while its interaction with $lnDTF$ remains virtually unchanged) and a more uncertain role of ICTs (ICT's coefficients are less precisely estimated in column (7)).

Table 4 around here

In Table 5, we test the sensitivity of our main results when using three different and disaggregated measures for each I4.0 technology, i.e. we estimate Eq. (4) including disaggregated measures for AIRs, AM and IIoT. In column (1) we only consider the direct relationship between AIR adoption on TFP growth, which results positive and statistically significant at the 10% level. When we also consider the ($AIR \times lnDTF$) interaction term in column (2), we observe a positive direct effect of AIR investments, which increases in magnitude, and a negative sign for the interaction term (both statistically significant at the 10% level). This result suggests similar implications as for the I4.0 variable: while AIRs spur TFP gains across manufacturing industries, these gains are larger for

[10] The model described in Section 3 assumes that it is not the identity of the technology frontier that is relevant in Eq. (4), but the distance from the frontier itself, capturing the potential for technological catch-up. As the model allows for any country to switch endogenously from being a frontier to a non-frontier country and vice versa, only requiring that the $lnDTF$ term correlates with the potential for technology transfer and productivity gains from catching-up. Thus, in column (8) we test an alternative specification of our model in which we measure $lnDTF$ using the average TFP level for the two countries featuring the highest value as the frontier, and by computing ΔlnA_F as the average growth rate between these two countries.

European economies closer to the frontier as AIRs do not favour additional catching-up mechanisms.

Columns (3) and (4), (5) and (6) replicate the same specifications considering the adoption of AM and IIoT, respectively. While our results for both the main and the moderated relationships are qualitatively unchanged across specifications reported in Table 5 as compared to the main results of Table 4, the estimates presented in columns (2), (4) and (6) of Table 5 highlight that each specific I4.0 technology exerts a different (in magnitude) direct effect on TFP growth and catching-up from the frontier.

Table 5 around here

5.2. Quantitative importance of the estimated effects

In this Section, we focus on the interpretation of the estimated coefficients – which represent rates of return (see, for instance, Griffith et al., 2004) – and on their quantitative importance.

Figure 1 around here

The average marginal effect of I4.0 adoption on TFP growth rates across all countries and sectors in our sample computed as $\alpha_3 + \alpha_4 \times \overline{lnDTF}$ is positive (i.e., 0.329–0.313×0.899=0.047), based on estimates from column (7) of Table 4, meaning that a 10% increase in I4.0 adoption implies a positive average marginal effects across all countries and manufacturing industries in our sample of +0.047 percentage points (pp). To get a more in-depth view, Figure 1 plots the marginal effects of adoption, considering heterogeneity across countries. The box-plot graph shows, for each country, the mean, the median, the interquartile range and the upper and lower adjacent values (excluding outliers).

Between 2009 and 2019, imports of I4.0 technologies had a positive effect on TFP growth in many sectors and countries in our sample. In 5 out of 14 countries (i.e., Germany, the UK, France, Italy and Spain), the adoption of I4.0 technologies has boosted productivity growth in virtually all manufacturing industries. In the Netherlands, about 75% of the sector-year distribution experienced positive gains, together with just more than 50% of the distribution for Austria, Belgium and Sweden. Conversely, in Finland and Czech Republic, more than 50% of the sector-year distribution experienced a negative effect on TFP growth rates. Denmark, Portugal and Slovakia were the European countries less able to harness benefits from the I4.0 adoption, with about 75% of sector-year observations showing a negative effect on TFP growth.[11]

In quantitative terms, more developed countries like Germany, the UK, France and Italy experienced a positive average (black dots) marginal effects across all manufacturing industries ranging between +0.1 pp and +0.18 pp associated with a 10% increase in I4.0 adoption. Conversely, Portugal and Slovakia suffered a negative average marginal effect, mild in the case of Portugal (i.e., about –0.024 pp), more severe for Slovakia (i.e., about –0.062 pp).

Figure 2 explores differences in the average marginal effect of adopting each I4.0 technology singularly (i.e., AIRs, AM and IIoT) on TFP growth, based on estimates from columns (2), (4) and (6) of Table 5. Decomposing the aggregate measure helps identifying which technology of the 4IR has contributed more, on average, to productivity growth between 2009 and 2019. Our estimates highlight that a 10% increase in the adoption of AIRs resulted in about +0.194 pp rise in TFP growth (black dot), while the same increase in AM adoption spurred a mean growth of about +0.308 pp. The lower contribution we estimate is associated with IIoT adoption (i.e., +0.062 pp, on average). In the case of AIRs and IIoT, the estimated marginal effects are positive for the large majority of the country-sector distribution (i.e., more than 75%): productivity gains from the former

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[11] While such result may be related to the yet mentioned lack of necessary conditions (e.g., a certain level of absorptive capacity) in the case of Slovakia and, to a certain extent, Portugal, the findings for Denmark may relate to the sectoral composition of the country, with a small and decreasing share of manufacturing as compared to services (similarly to other Nordic countries in our sample, i.e. Sweden and Finland).

spans over a larger positive range (i.e., up to about +0.7), while those associated with the latter are much lower (i.e., only up to about +0.22 pp). Most strikingly, our results highlight that AM adoption boosted TFP growth across European manufacturing industries the most amongst I4.0 technologies investigated: even the bottom percentiles of the distribution experienced moderate positive marginal effects and TFP gains above the 25th percentile of the distribution range between +0.23 and +0.55 pp.

Compared to previous studies, our results on AIR and IIoT adoption are on average more conservative, but in line with evidence from Graetz and Michaels (2018) and Edquist et al. (2019). To the best of our knowledge, so far there is no evidence on the relationship between AM adoption and productivity measures and this work represents the first attempt of quantifying AM contribution to TFP growth.

Figure 2 around here

In Figure 3, we further delve into the heterogeneity of effects associated with each different I4.0 technology by plotting marginal effects for the European countries considered here. In the case of AIRs and IIoT, most countries enjoyed net TFP gains from their adoption above the 25th percentile of the distribution. Only Portugal and Slovakia present a consistent portion of their sector-year distribution (i.e., about 50% or more) experiencing negative marginal effects of TFP growth. However, TFP gains and losses from IIoT adoption spans over a narrower range compared to that resulting from AIR adoption. Furthermore, almost all countries and sectors experience positive marginal effects from AM adoption (except the bottom percentiles of the Slovak distribution), reflecting the pattern seen in Figure 2.

To conclude, findings presented in Figure 3 suggest that AM adoption spurs a more homogeneous overall positive effect on productivity growth across countries and manufacturing sectors, i.e. accounting for both the direct adoption effect and indirect effect by facilitating (or hampering) catching-up mechanisms. Moreover, the effect of AIRs and IIoT is positive for most (if not all) sectors in European countries closer to the technology frontier and negative in many industries in laggard countries.

Figure 3 around here

5.3. Robustness checks

Endogeneity: The first concern might relate with the effect of 4IR technologies on TFP growth rates not being properly estimated by our main econometric strategy. Specifically, it could be overestimated because firms operating within sectors in our sample might import, invest in, and adopt more I4.0 technologies in periods of faster productivity growth. Since our specifications in Tables 4 and 5 highlight a strong correlation between our measures proxying the I4.0 adoption and TFP growth, we need to be cautious in interpreting our results as causal, as we cannot rule out reverse causality. To address this issue, we employ the (System-)GMM estimator (Blundell and Bond, 1998) considering all our regressors as endogenous, and instrumenting them with their appropriate lags (i.e., lags one and two).[12] Since it assumes that current shocks in the error term do not affect lagged values of the regressors and that lagged values of the regressors do not directly affect current values of the dependent variable, the GMM estimator is particularly efficient to deal with reverse causality. Although we acknowledge that using external instruments would be the ideal option to deal with endogeneity, we also recognise that it is difficult to find appropriate exogenous instruments for the adoption of both I4.0 technologies overall and for each specific technology, varying across countries, sectors and years. For this reason, the traditional instrumental variables approach may not efficiently solve our potential endogeneity issues.

[12] We followed Roodman (2009) guidelines in the choice of the number of instruments.

Some studies (e.g., Bogliacino et al., 2012) highlight that GMM estimator perform poorly when the panel is characterised by a low number of units (like the 176 country-sector units in our study), as additional check we employ Bruno's (2005) Least Squares Dummy Variable Corrected (LSDVC) estimator, which is initialised by a GMM estimator and then recursively corrects the bias of the FE estimator. We confirm statistical significance by computing bootstrapped standard errors (50 iterations). Finally, we further test the consistency of the GMM estimator by computing the Feasible Generalized Least Square (FGLS) estimator (Parks, 1967). Beyond heteroscedasticity across panels and panel-specific serial correlation, the FGLS estimator also control for cross-sectional dependence, which may lead to more efficient estimates (Chen et al., 2010). Table C2 in Appendix C shows estimates replicating the main specifications from Tables 4 and 5, highlighting qualitatively similar and statistically robust results, thus indicating our main estimates not to be affected by reverse causality issues.

Alternative I40 variables: Our main explanatory variables capturing overall I4.0 adoption and the adoption AIRs, AM and IIoT at the sector level are built as exposure measures, by accounting for the existing linkages between aggregate I4.0 imports and sectoral trade patterns. Despite these variables should proxy true sectoral imports of 4IR technologies, not otherwise available, their construction is based on the assumption that the I4.0 adoption of each industry is proportional to its use of I4.0-related inputs sourced from I4.0 producing sectors from every other country. To provide further robustness to our main results, we relax this assumption and use observed I4.0 imports at the country level as a measure of adoption. We estimate specifications of the model described in Eq. (4) in which our adoption variables only exploit variation across countries and time. This implies that, differently from our main results, these estimates should be interpreted only as the average relationship between I4.0 technology adoption and TFP growth across countries. Table C3 in Appendix C presents estimates replicating specifications in Tables 4 and 5.

Additionally, we check the sensitivity of the main results by estimating Eq. (4) including sectoral measures of I4.0 technology adoption computed using sectoral depreciation rates specific for each type of capital, as provided by EU KLEMS (results are reported in Table C4 in Appendix C). Specifically, we used the depreciation rate for machinery and equipment "*OMach*" for computing our AIR and AM variables, and alternatively (a) the average of sectoral depreciation rates for information technologies "*IT*" (0.315), computing technologies "*CT*" (0.115) and software and databases "*Soft_DB*" (0.315), which results in a depreciation rate of 0.248, and; (b) a fixed depreciation rate of 0.315, for computing our IIoT variable. Results are qualitatively unchanged and statistically robust, confirming our main findings.

Alternative TFP growth measure: In our econometric analysis we account for two main factors which might lead to deviations from real patterns when measuring TFP growth (i.e., differences in hours worked and skill composition). Likewise, we acknowledge that there are other potential sources of measurement error which might affect the measurement of TFP growth rates. In order to provide robustness the adopted methodology to measure TFP growth (Caves et al., 1982) and to our main results by using an alternative approach, we use data on TFP growth rates provided by EU KLEMS[13] to measure our dependent variable ΔlnA_{ijt} and one of the explanatories (i.e., TFP growth at the frontier, ΔlnA_{Fjt}). Table C5 in Appendix C reports estimates comparable to that in Tables 4 and 5: our main results are robust to the use of this alternative measure. Nonetheless, we note that using EU KLEMS' TFP growth measure as dependent variable – which better accounts changes in for skills, hours worked and capital inputs – results in much larger coefficients for the distance-to-frontier ($lnDTF$) term, for the ICT variable and for their interaction term (also, more stable and statistically significant for the ICT and for the ($ICT \times lnDTF$) variables). Conversely, the large contribution to TFP growth from R&D investments observed in our main estimates here

[13] Computed following the growth accounting approach as described Stehrer et al. (2019).

appears to be limited. This potentially suggests that the effect of ICT investments and catching-up is underestimated in our baseline results, while that of R&D might be overestimated.

Unweighted/differently weighted regressions: Our main results are estimated through WLS-FE (i.e., using the within-groups estimator). We use industry-level shares of value added in total economy to account for differences in size across manufacturing industries and in their relative weight on total economy when compared across countries. Thus, our model implies that I4.0 adoption might have a relatively more important role in some sectors, depending on their relative importance in the whole economy. To further test the robustness of our main results, in Table C6 in Appendix C we report estimates from unweighted regressions, estimated through OLS-FE (comparable to those reported in Tables 4 and 5). In so doing, we test the less restrictive assumption that all sectors have the same relative weight across countries.

Additionally, we also test for the sensitivity of our main results by estimating weighted regressions using industry-level shares of employment in total economy as weights (Table C7 in Appendix C shows results comparable to those reported in Tables 4 and 5). Our main findings are robust to these further checks.

Additional checks: Finally, we checked for the sensitivity of our main results by excluding country-sector-year observations presenting extreme values (i.e., outliers) and excluding initial years (i.e., 2009 and 2010) in order to eliminate the potential bias associated to the potential overshooting of industry-level TFP growth after the 2008 global financial crisis. Results are qualitatively unchanged and available upon request.

6. Discussion and conclusions

Total factor productivity has been stagnating across European economies ever since the second half of the 90s and throughout the early 2000s as a result of the inability of European countries to harness the benefits of investments R&D, human capital accumulation and the diffusion of ICTs

(Mc Morrow et al., 2008). Overall economic convergence has been hampered by institutional factors (e.g., weak policy), existing structural rigidities and the economic downturns observed in Europe after the 2008 global financial crisis (ECB, 2015; Bergeaud et al., 2016; Eurofound, 2020), culminating in 2020 with the Covid-19 pandemic. This evidence signs a clear break with the pattern of TFP growth and convergence observed in several empirical works looking at earlier decades, i.e. between the 70s and early 90s (Griffith et al., 2004; Cameron et al., 2005). Similarly, recent firm-level studies reaffirm this pattern by highlighting an ongoing process of divergence between most productive and laggard firms (Andrews et al., 2019; Pompei and Venturini, 2022).

This study investigates to what extent the adoption of I4.0 technologies could contribute to end this pattern of sluggish productivity growth. Our results suggest that I4.0 technologies could play an important role in the long-run to reverse the observed productivity growth stagnation. However, we find that gains related to the rising adoption of embodied 4IR technologies are unevenly distributed across Europe, with countries closer to the technology frontier benefitting more, while technological laggards seem unable to exploit I4.0-enabled technology transfer. For instance, one of the most technologically advanced European economies, Germany, is a leading actor in I4.0 (UNIDO, 2018; Martinelli et al., 2021). Conversely, other European countries like Portugal and Slovakia still lag behind in the adoption of enabling technologies, in the development of 4IR-related competences and in the implementation of dedicated policies (Ciffolilli and Muscio, 2018; Corradini et al., 2021). Overall, this hampers productivity gains potentially deriving from investments in I4.0 and may contribute to widen the productivity gap between more developed and laggard countries, ultimately increasing inequality across European countries.

Furthermore, our analysis sheds light on the heterogeneous productivity effects of different technologies, offering estimates based on comparable adoption measures. Our results on AIRs and IIoT are in line with evidence from previous studies (Graetz and Michaels, 2018; Edquist et al., 2019), although we find more conservative estimates of the associated productivity gains. At the same time, to the best of our knowledge, our work provides a first quantification of productivity gains deriving from the adoption of AM. Notably, our results suggest such gains to be positive and quantitatively important as much as that coming from AIRs.

Contextualised in our DTF framework, the adoption of AIRs and AM seem to bring larger contributions to productivity gains across European manufacturing sectors, while TFP growth coming from IIoT adoption is found to be lower. Furthermore, while such gains are more evenly distributed across countries in the case of AM (suggesting the technology can facilitate catching-up for lagging countries), only most technologically advanced economies (closer to the technology frontier) are found to benefit from AIRs and IIoT adoption. Potential reasons behind these results might relate with either the level of technological maturity associated with different I4.0 technologies or with the differences in the associated investment costs, acting as a barrier.[14] Chiacchio et al. (2019) and Martinelli et al. (2021) also discuss how high investment costs and lack of sufficient absorptive capacity remain two of the main factors limiting the adoption of these technologies, especially for SMEs, while large companies (mostly multinationals) are better suited to efficiently adopt 4IR technologies.

Another barrier to the adoption of 4IR technologies is the lack of precise and unified standards (above all, technical) across countries and industries (Martinelli et al., 2021), enabling interoperability between different technologies. While leading producers sponsor proprietary standards, adopters ask for more open and universal standards like the Reference Architectural Model Industrie 4.0 (Schweichhart, 2017) or alternatives emerging under the supervision of international bodies like the International Telecommunication Union (ITU) or the ISO. This issue is

[14] According to estimates from Acemoglu and Restrepo (2020), the average price of AIR ranges between 50,000 and 100,000 USD, while the average price for an industrial AM machine is between 200,000 and 250,000 USD according to our computations based on data from all major AM producers worldwide and reported by Senvol. Senvol's data are available at http://senvol.com/machine-search/. Concerning IIoT, the total cost of deployment greatly varies depending on the sector and on the scale of the project. Using total cost of ownership (TCO) calculator for IoT applications by NOKIA, we estimate cost for a medium-sized factory to range between 1.6mln and 0.8mln USD. NOKIA's IoT TCO calculator is available at https://pages.nokia.com/T007K9-Compare-Wireless-Critical-Connectivity-Options.

particularly important for IIoT, given its crucial and infrastructural role within the I4.0 architecture (Atzori et al., 2010).

Finally, this paper also adds to the literature on investment-specific technological change (Greenwood et al., 1997, 2000), which recognises the role of capital investments in specific types of machinery and equipment as one of the most relevant sources of productivity growth. Since, from an empirical standpoint, we model the technological change associated with I4.0 by studying the adoption of the new technologies of the 4IR, embodied in capital goods, our work goes along several studies looking at the role played by ICT (vs non-ICT) investments in determining productivity growth (Bakhshi and Larsen, 2005; Chung, 2018; Martínez et al., 2010; Venturini, 2015). Just as we found here, these works highlight how investments in technologies like ICTs bring productivity effects which are not fully measured *via* growth accounting due to excess returns beyond capital accumulation (Edquist and Henrekson, 2017; Hulten, 2010). Furthermore, this paper contributes to the debate on the source of differences in productivity across countries and their implications for economic and technological convergence (Bergeaud et al., 2016; Cameron et al., 2005; Griffith et al., 2004; Madsen et al., 2010; Mason et al., 2020; Minniti and Venturini, 2017).

6.1. Policy implications

The above discussion leads directly to the debate on whether the bulk of dedicated I4.0 policy initiatives put in place by European countries over the last decade has led to significant results in boosting the diffusion of such advanced technologies (lately, the 2021-2026 Next Generation EU initiative launched in the aftermath of the Covid-19 pandemic). While more traditional top-down, science-driven industrial policies may still be relevant, it becomes paramount to boost policy incentives fostering innovation and I4.0 adoption across SMEs. This would bring more widespread benefits across European economies, given the major role played by these firms: a more integrated approach across different technologies must go along with dedicated incentives and approaches for individual technologies, which are more exposed to inefficient implementation.

At the same time, these initiatives need to be paired with a broader recognition among policymakers that integrating economic incentives with local dissemination of competencies and specific I4.0 knowledge content. For instance, the creation of industry-university clusters would provide the adequate stock of skills to the local workforce, tax credits would boost private R&D spending, infrastructural investments (e.g., high-speed broadband connections, 5G) would boost technology adoption by providing enabling conditions for more advanced I4.0 systems. All these actions eventually promoting knowledge transfer and resulting in faster and more effective technology diffusion. Similarly, coordinated national and regional policies across the continent (i.e., following a common framework and standards) would create the potential for larger gains, not confined to productivity growth alone but also in terms of aggregate economic growth and better employment conditions in the decades ahead.

6.2. Limitations and future research

Our findings should be considered under the light of the caveats that characterise our analysis: as trade data for highly disaggregated products are not directly available at the industry level, we can only link them to the importing sector by means of input-output tables, i.e. by creating proxies of sectoral adoption. This is a limitation of our approach as compared to studies exploiting purely sectoral variables (e.g., Du and Lin, 2022; Graetz and Michaels, 2018). Nonetheless, these studies focus on a single technology, while our research follows an established approach (e.g., Acemoglu and Restrepo, 2020; Felice et al., 2022) and offers the advantage of a cross-country and cross-sector perspective on the effects of adopting multiple (embodied) I4.0 technologies on TFP growth.

Furthermore, we acknowledge that our I4.0 adoption measures are based on import data alone. At the same time, more developed European countries also feature as major producers of these technologies worldwide (e.g., Germany's KUKA and EOS producer; see also Castellani et al., 2022). Since our findings highlight that more technologically advanced countries, like Germany, are those benefitting the most from I4.0 adoption, we recognise that our estimates could underestimate the real impact of these technologies across I4.0 producing countries. However, following Caselli and Coleman (2001), two proxies adoption can be calculated: imports of AMT capital goods, and $net\ consumption = (production + import - export)$. The latter accounts for two sources of capital investments determining adoption of AMTs, that is domestic and foreign production. Nevertheless, Castellani et al. (2022) show that the two measures of adoption are highly correlated at the country level. Since the second measure is not available for all countries and technologies considered, as production data on goods embodying AMTs are in some cases missing or not reliable, we rely on the proxy based on imports.

Since our import-based measure of I4.0 adoption provides robust results which are in line with prior findings in the literature, it could be used to delve into several possible avenues for future research. Since import data at the fine-grained product level are available for a growing number of countries and for long and constantly updated time series, our measure is scalable and can be used to analyse larger samples of countries and industries. Furthermore, international transaction-level data are available and increasingly accessible in many countries. This can allow an extension of this analysis to the firm level, possibly linking adoption of 4IR technologies to firm productivity, international competitiveness, offshoring and reshoring or employment dynamics and composition.

Further research in this area might investigate the role of different contextual conditions in explaining why we witness heterogeneous results in the way European countries benefits from I4.0 adoption. As discussed above, following the wave of I4.0 policy initiatives introduced by European countries during latest years, incentives targeted more towards some technologies than others might have had a role in explaining the differences documented here. Another interesting direction of research should investigate the underlying mechanisms at place, which might either help or hinder productivity effects of 4IR technology adoption, such as the degree of capital/labour complementarity featured by each of these technologies.

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Tables and Figures

Table 1. Summary statistics of the main variables

	ΔlnA_{ijt}	ΔlnA_{Fjt}	$lnDTF_{ijt-1}$	RD_{ijt-1}	M_{ijt-1}	ICT_{ijt-1}	$I40_{ijt-1}$	AIR_{ijt-1}	AM_{ijt-1}	$IIoT_{ijt-1}$
Mean	0.0082	0.0165	0.8992	0.0599	4.2768	0.0973	0.2436	0.3438	0.3583	0.2368
SD	0.0610	0.0844	0.3298	0.0938	24.2155	0.3909	0.2212	0.2394	0.4750	0.2190
Max	0.8993	0.6955	2.0327	1.8348	981.4395	15.6755	1.4864	2.7346	6.0443	1.4432
Median	0.0035	0.0064	0.9295	0.0299	2.1856	0.0648	0.1692	0.2667	0.2068	0.1637
Min	-0.4817	-0.1321	0.1303	-0.0043	0.2567	0.0003	0.0007	0.0013	0.0005	0.0007

Notes: Sample size for all variables is 1,760 observations over the 2009–2019 period. Table C1 in Appendix C reports a full description of how variables are defined. ΔlnA_{ijt}, ΔlnA_{Fjt} and $lnDTF_{ijt-1}$ variables include controls for differences in hours worked and skill composition. We discuss potential multicollinearity concerns in Appendix B.

Table 2. Panel unit root test

Variables	Im, Pesaran and Shin (2003): Integration order I(1)		
	t	Standardised *t*	*p*-value
ΔlnA_{ijt}	-3.8361	-17.2055	0.0000
ΔlnA_{Fjt}	-2.2471	-7.8142	0.0000
$lnDTF_{ijt-1}$	-3.4265	-15.5618	0.0000
RD_{ijt-1}	-2.8077	-10.0887	0.0000
M_{ijt-1}	-2.5229	-9.1750	0.0000
ICT_{ijt-1}	-2.3497	-5.9674	0.0000
$I40_{ijt-1}$	-2.3239	-5.2674	0.0000
AIR_{ijt-1}	-2.1187	-2.4660	0.0068
AM_{ijt-1}	-3.4108	-14.8992	0.0000
$IIoT_{ijt-1}$	-3.4433	-14.9749	0.0000

Notes: AR parameter is assumed to be panel-specific, panel means and time trend are included. Critical values for *t* are: -2.420 (1%), -2.340 (5%), -2.300 (10%). The null hypothesis is that all panels have a unit root. The alternative hypothesis is that the fraction of panels that are stationary is non-zero. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3. Panel cointegration test

Pedroni (2004)	*t*	*p*-value
Common AR parameter		
PP ($I40_{ijt-1}$ regressions)	-53.3666	0.0000
ADF ($I40_{ijt-1}$ regressions)	-45.7697	0.0000
PP (AIR_{ijt-1} regressions)	-51.9008	0.0000
ADF (AIR_{ijt-1} regressions)	-45.2471	0.0000
PP (AM_{ijt-1} regressions)	-43.2549	0.0000
ADF (AM_{ijt-1} regressions)	-38.5914	0.0000
PP ($IIoT_{ijt-1}$ regressions)	-43.0745	0.0000
ADF ($IIoT_{ijt-1}$ regressions)	-37.6625	0.0000
Panel-specific AR parameter		
PP ($I40_{ijt-1}$ regressions)	-63.5133	0.0000
ADF ($I40_{ijt-1}$ regressions)	-52.5356	0.0000
PP (AIR_{ijt-1} regressions)	-59.5140	0.0000
ADF (AIR_{ijt-1} regressions)	-51.0050	0.0000
PP (AM_{ijt-1} regressions)	-51.2505	0.0000
ADF (AM_{ijt-1} regressions)	-43.6695	0.0000
PP ($IIoT_{ijt-1}$ regressions)	-49.1412	0.0000
ADF ($IIoT_{ijt-1}$ regressions)	-43.4648	0.0000

Notes: The null hypothesis is no cointegration. The alternative hypothesis is that the variables are cointegrated in all panels.

Table 4. WLS-FE estimates: relationship between sectoral I4.0 technology adoption and TFP growth

	1995-2019	1995-2008	2009-2019					
ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔlnA_{Fjt}	0.163***	0.199***	0.257***	0.258***	0.258***	0.021	0.029	0.299***
	(0.030)	(0.047)	(0.036)	(0.036)	(0.035)	(0.050)	(0.057)	(0.092)
$lnDTF_{ijt-1}$	0.102***	0.167***	0.243***	0.244***	0.238***	0.207***	0.223***	0.311***
	(0.012)	(0.026)	(0.036)	(0.036)	(0.036)	(0.029)	(0.037)	(0.042)
RD_{ijt-1}	0.177***	0.134***	0.282***	0.282***	0.243***	0.892***	1.236***	1.274***
	(0.039)	(0.045)	(0.071)	(0.071)	(0.067)	(0.173)	(0.250)	(0.216)
$(RD \times lnDTF)_{ijt-1}$	-0.248***	-0.175**	-0.965***	-0.970***	-0.849***	-0.874***	-1.150***	-1.228***
	(0.070)	(0.075)	(0.237)	(0.239)	(0.235)	(0.195)	(0.254)	(0.240)
M_{ijt-1}	-0.001**	0.004	-0.003***	-0.003***	-0.004***	-0.005***	-0.010***	-0.009***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
$(M \times lnDTF)_{ijt-1}$	0.002**	-0.004	0.006***	0.006**	0.007***	0.005***	0.008***	0.009***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
ICT_{ijt-1}	0.052**	0.045	0.197***	0.189***	0.216***	0.181	0.491**	0.465**
	(0.025)	(0.037)	(0.061)	(0.058)	(0.045)	(0.129)	(0.234)	(0.198)
$(ICT \times lnDTF)_{ijt-1}$	-0.083*	-0.046	-0.387***	-0.379***	-0.400***	-0.157	-0.526*	-0.568**
	(0.046)	(0.055)	(0.143)	(0.137)	(0.114)	(0.163)	(0.279)	(0.262)
$I40_{ijt-1}$				-0.007	0.292***	0.206***	0.329***	0.311***
				(0.029)	(0.057)	(0.059)	(0.102)	(0.089)
$(I40 \times lnDTF)_{ijt-1}$					-0.544***	-0.247***	-0.313***	-0.323***
					(0.096)	(0.059)	(0.089)	(0.087)
TFP controls	-	-	-	-	-	s	h,s	h,s,2c
Observations	4,048	2,291	1,757	1,757	1,757	1,757	1,760	1,760
R-squared (within)	0.488	0.577	0.423	0.422	0.439	0.324	0.305	0.339

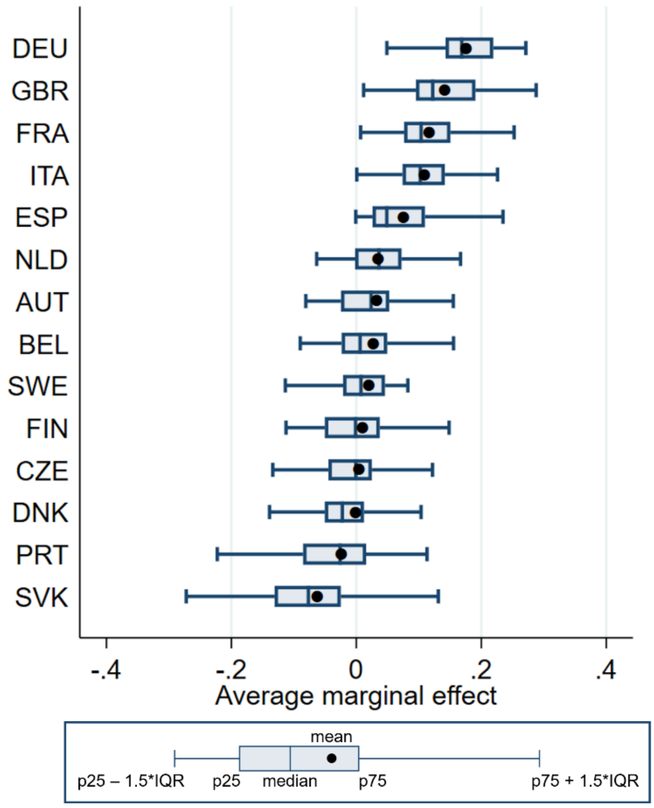
Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using value added shares in total economy as weights. TFP controls are h: hours worked; s: skill composition; 2c: two-country frontier. The dependent variable is the growth rate of TFP. ΔlnA_{Fjt} is the contemporaneous growth rate of TFP for the frontier; $lnDTF_{ijt-1}$ is the lagged distance from the technology frontier; RD_{ijt-1} is the lagged sectoral share of R&D stock in value added; M_{ijt-1} is lagged sectoral share of imports in value added; ICT_{ijt-1} is lagged sectoral share of ICT stock in value added; $I40_{ijt-1}$ is lagged sectoral share of I4.0 technologies import stock in value. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5. WLS-FE estimates: relationship between sectoral AIR, AM and IIoT adoption measures and TFP growth

ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)
ΔlnA_{Fjt}	0.032	0.030	0.029	0.034	0.029	0.030
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
$lnDTF_{ijt-1}$	0.191***	0.202***	0.188***	0.209***	0.197***	0.219***
	(0.035)	(0.037)	(0.032)	(0.033)	(0.035)	(0.039)
RD_{ijt-1}	1.270***	1.323***	1.208***	1.260***	1.294***	1.254***
	(0.245)	(0.254)	(0.242)	(0.237)	(0.248)	(0.250)
$(RD \times lnDTF)_{ijt-1}$	-1.180***	-1.226***	-1.139***	-1.162***	-1.210***	-1.163***
	(0.249)	(0.256)	(0.245)	(0.235)	(0.252)	(0.254)
M_{ijt-1}	-0.009***	-0.011***	-0.005*	-0.008***	-0.009***	-0.010***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
$(M \times lnDTF)_{ijt-1}$	0.007***	0.010***	0.004	0.006**	0.008***	0.008***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ICT_{ijt-1}	0.435**	0.538**	0.189	0.357**	0.464**	0.493**
	(0.215)	(0.247)	(0.165)	(0.171)	(0.195)	(0.198)
$(ICT \times lnDTF)_{ijt-1}$	-0.481*	-0.589**	-0.250	-0.445*	-0.515**	-0.530**
	(0.265)	(0.296)	(0.213)	(0.234)	(0.249)	(0.247)
AIR_{ijt-1}	0.267*	0.788*				
	(0.160)	(0.424)				
$(AIR \times lnDTF)_{ijt-1}$		-0.661*				
		(0.401)				
AM_{ijt-1}			0.024	0.596***		
			(0.017)	(0.193)		
$(AM \times lnDTF)_{ijt-1}$				-0.320***		
				(0.109)		
$IIoT_{ijt-1}$					0.081**	0.248***
					(0.034)	(0.076)
$(IIoT \times lnDTF)_{ijt-1}$						-0.207***
						(0.068)
TFP controls	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,760	1,760	1,760	1,760	1,760	1,760
R-squared (within)	0.291	0.298	0.287	0.309	0.295	0.302

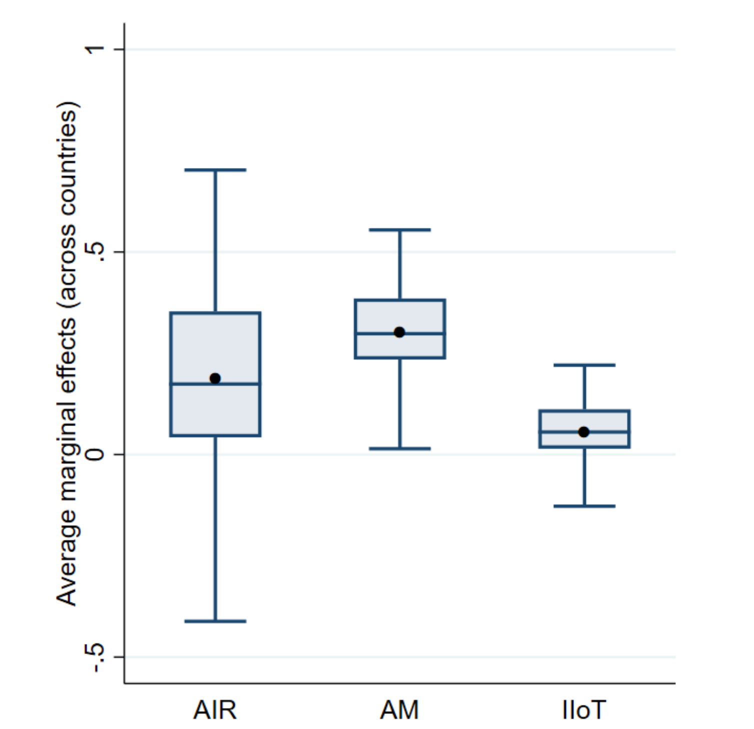
Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using value added shares in total economy as weights. TFP controls are h: hours worked; s: skill composition. The dependent variable is the growth rate of TFP. ΔlnA_{Fjt} is the contemporaneous growth rate of TFP for the frontier; $lnDTF_{ijt-1}$ is the lagged distance from the technology frontier; RD_{ijt-1} is the lagged sectoral share of R&D stock in value added; M_{ijt-1} is lagged sectoral share of imports in value added; ICT_{ijt-1} is lagged sectoral share of ICT stock in value added; AIR_{ijt-1} is lagged sectoral share of advanced industrial robots import stock in value added; AM_{ijt-1} is lagged sectoral share of additive manufacturing import stock in value added; $IIoT_{ijt-1}$ is lagged sectoral share of industrial internet of things import stock in value added. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Marginal effect of I4.0 technology adoption on TFP growth rates, by country



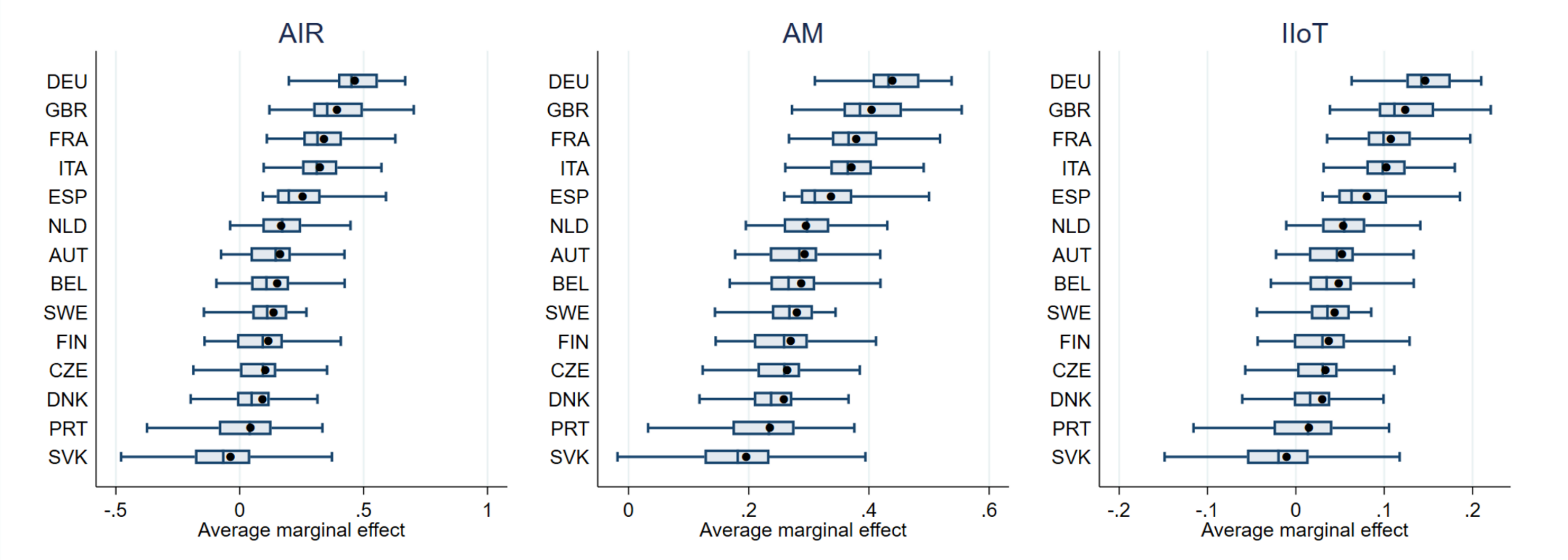
Notes: Authors' own estimates. Average marginal effects of I4.0 technology adoption on TFP growth rates computed as $\alpha_3 + \alpha_4 \times lnDTF_{ijt}$, using $\alpha_3 = 0.329$ and $\alpha_4 = -0.313$ from column (7) of Table 4. The black dot indicates the mean value across sectors; the line inside the box indicates the median sector; the box shows the interquartile range (IQR); the extreme values are the lower adjacent value (25th %ile – 1.5*IQR) on the left and the upper adjacent value (75th %ile + 1.5*IQR) on the right; outliers are excluded.

Figure 2. Marginal effect of AIR, AM and IIoT adoption on TFP growth rates



Notes: Authors' own estimates. Average marginal effects of AIR, AM and IIoT adoption on TFP growth rates computed as $\alpha_3 + \alpha_4 \times lnDTF_{ijt}$, using $\alpha_3^{AIR} = 0.788$ and $\alpha_4^{AIR} = -0.661$ from column (2) of Table 5, $\alpha_3^{AM} = 0.596$ and $\alpha_4^{AM} = -0.320$ from column (4) of Table 5, and $\alpha_3^{IIoT} = 0.248$ and $\alpha_4^{IIoT} = -0.207$ from column (6) of Table 5. The black dot indicates the mean value across sectors; the line inside the box indicates the median sector; the box shows the interquartile range (IQR); the extreme values are the lower adjacent value (25^{th} %ile – 1.5*IQR) on the left and the upper adjacent value (75^{th} %ile + 1.5*IQR) on the right; outliers are excluded.

Figure 3. Marginal effect of AIR, AM and IIoT adoption on TFP growth rates, by country



Notes: Authors' own estimates. Average marginal effects of AIR, AM and IIoT adoption on TFP growth rates computed as $\alpha_3 + \alpha_4 \times lnDTF_{ijt}$, using $\alpha_3^{AIR} = 0.788$ and $\alpha_4^{AIR} = -0.661$ from column (2) of Table 5, $\alpha_3^{AM} = 0.596$ and $\alpha_4^{AM} = -0.320$ from column (4) of Table 5, and $\alpha_3^{IIoT} = 0.248$ and $\alpha_4^{IIoT} = -0.207$ from column (6) of Table 5. The black dot indicates the mean value across sectors; the line inside the box indicates the median sector; the box shows the interquartile range (IQR); the extreme values are the lower adjacent value (25th %ile – 1.5*IQR) on the left and the upper adjacent value (75th %ile + 1.5*IQR) on the right; outliers are excluded.

Appendix A: Alternative TFP measures

We compute different TFP measures, correcting for two different characteristics which may be sources of cross-country differences: (a) we adjust the measure of labour inputs for differences in the skill composition of the workforce; (b) we adjust the measure of labour inputs for differences in hours worked.

Differences in the skill composition of the workforce: Our baseline TFP measures uses the number of people employed in sector j of country i as a measure of the labour input in the production function. First, we control for differences in the quality of the labour inputs. Using a similar index to that proposed by Griffith et al. (2004), we express employment in each country, sector, and year as:

$$L_{ijt} = \left(E_{ijt} \times H\_h_{ijt}\right)^{W\_h_{ijt}} \times \left(E_{ijt} \times H\_m_{ijt}\right)^{W\_m_{ijt}} \times \left(E_{ijt} \times H\_l_{ijt}\right)^{W\_l_{ijt}} \tag{A1}$$

where E_{ijt} denotes the number of people employed in sector j of country i, at time t; H_h_{ijt}, H_m_{ijt} and H_l_{ijt} denote shares of hours worked by employees with high, medium and low education level across manufacturing sectors, respectively; W_h_{ijt}, W_m_{ijt} and W_l_{ijt} denote shares of workers with high, medium and low education level in the wage bill across manufacturing sectors, respectively. Since our analysis only covers manufacturing industries and information on the skill composition of the workforce in EU KLEMS dataset are available only at the 1-digit level of sectoral aggregation (i.e., the whole manufacturing), shares of hours worked and wages by employees with different education are proportionally derived by weighting 1-digit manufacturing data on composition by the share of hours worked in each 2-digit manufacturing industry.

Differences in hours worked: The second adjustment we make is using the number of hours worked by people employed. This is a sector-specific adjustment.

Appendix B: Identification of I4.0-related product codes

As explained in Section 4.2, we use highly disaggregated data (at the 8-digit level) on the value of import flows from Eurostat's Comext data set. A complete overview of the identification procedure for selecting the CN product codes strictly related to Industry 4.0 (I4.0), of the technical caveats associated with Comext data, and of the validation process corroborating the selected product codes is described in Castellani et al. (2022). In sum, the procedure followed these steps:

1. Analysis of different sources of information to gather knowledge and understanding of the technologies of interest (e.g., standard international terminology approved by ASTM International and International Organisation for Standardization (ISO) for AM technologies, concepts and definitions on IIoT provided by International Telecommunication Union (ITU); product catalogues of worldwide leaders in I4.0 production and sales; the World Customs Organisation (WCO) and Eurostat);
2. Definition of a set of keywords capturing technological characteristics, machinery, equipment, and components associated with I4.0 technologies, as well as related processes;
3. Use of keywords to identify product codes in the CN classification by means of matching with detailed product descriptions, subsequent screening of false-positive and false-negative matches at different levels of disaggregation (i.e., 8-, 6- or 4-digit codes) and final disambiguation of the 8-digit product codes strictly related to I4.0;
4. Validation of the identified CN product codes by: (a) means of a survey sent to 229 producers of industrial robots, additive manufacturing/3D printing machines, and industrial IoT and automation equipment in order to collect information on the CN product codes used by I4.0 producers when exporting their products worldwide; (b) consulting experts from the Italian Customs Agency and practitioners working at a private customs broker and logistic service provider operating in two Milan (IT) airports.

Table B1 below reports the detailed list of 8-digit CN product codes identified, 4-digit HS categories and product descriptions. Hereafter, we report for each technology considered in this work the 8-digit product categories embodying I4.0 technologies.

Advanced industrial robots: These capital goods are defined by the 6-digits HS code 847950 and the 8-digits CN code 84795000. In fact, no substantial difference exists between the 6- and the 8-digits product codes; hence, trade data associated with the two codes are fundamentally the same. This code was previously identified and used in other works (e.g., Acemoglu and Restrepo, 2022; Domini et al., 2021), providing confidence in its goodness. The authors also identify the 6-digits HS code 847989 as a further set of automatic and dedicated machinery potentially including industrial robots. Yet, by looking at more disaggregated product codes stemming from 847989, we find no 8-digits CN code specifically referring to alternative forms of advanced industrial robots of the type we are interested, but only references to older types of automatic machines. Thus, we only consider CN code 84795000.

Additive manufacturing: Seven different additive manufacturing processes having distinct technical characteristics, embodied in different types of machinery and using different types of material can be identified; these are: (1) binder jetting, (2) directed energy deposition, (3) material extrusion, (4) material jetting, (5) powder bed fusion, (6) sheet lamination and (7) vat photopolymerization. These capital goods are captured by different 8-digits CN codes. Machinery embodying processes (1) and (7) involve either the deposition of chemical liquid bonding agents or shaping objects by selectively curing liquid polymers with light and should be consistently captured by CN code 84778011 (Machines for processing reactive resins). Processes (2) and (5) require machines using focused thermal energy to melt materials as they are deposited on the building surface, or to selectively melt shapes on the surface of a powder bed composed of different materials (metallic, ceramic, etc.); the CN code including machinery adopting this process is CN code 84639000 (Machine tools for working metal or cermets, without removing material). Also, machinery adopting process (6) achieve the desired 3-dimensional object by bonding together sheets of material, usually metals, and should be traded under CN code 84639000. Finally, CN codes 84778019 and 84778099 refer to machinery for working plastic products, and other chemical materials (e.g., foam) and hence should capture capital goods embodying processes (3), (4), and partially (1) and (5), as they involve the extrusion of material and the deposition of either droplets of building or bonding materials, usually photopolymers, wax or foam.

Industrial internet of things: This category includes both 8-digits CN codes referring to intermediates and capital goods.[15] Specifically, capital goods referring to wireless sensors and actuators should be traded under CN codes 84718000 and 84719000 as they capture network communications equipment (e.g., hubs, routers, gateways) for LANs and WANs and other network and similar cards for automatic data processing machines. Non-wireless communication equipment should be captured by CN code 85176200 (Machines for the reception, conversion and transmission or regeneration of voice, images or other data, including switching and routing apparatus). CN codes 85269120 and 85269200 relates to radio navigational apparatus, receivers and controls, thus they should capture distributed systems such as RFID tag and GPS. Microchips (including NFC

[15] In identifying the product codes in which some capital and intermediate goods referring to IIoT are traded we refer to guidelines provided by Eurostat and available at https://trade.ec.europa.eu/tradehelp/classifying-computers-software.

chips) and integrated circuits are traded under CN codes 85423111, 85423119, 85423190, 85423911, 85423919 and 85423990. Automatic regulating or controlling instruments and apparatus used in industrial processes are traded under CN codes 90321020, 90321080, 90322000, 90328100 and 90328900.

Table B1. List of initially identified CN product codes related to I4.0 technologies

4-digits HS product codes, 8-digits CN product codes and CN product descriptions		
Advanced Industrial Robots		
8479	Machines and mechanical appliances having individual functions, not specified or included elsewhere in this chapter	
	84795000	Industrial robots, not elsewhere specified or included
Additive Manufacturing		
8463	Other machine tools for working metal or cermets, without removing material	
	84639000	Other machine tools for working metal or cermets, without removing material; Other
8477	Machinery for working rubber or plastics or for the manufacture of products from these materials, not specified or included elsewhere in this chapter	
	84778011	Machines for the manufacture of foam products; Machines for processing reactive resins
	84778019	Machines for the manufacture of foam products; Others
	84778099	Other machinery; Other; Other
Industrial Internet of Things		
8471	Automatic data-processing machines and units thereof; magnetic or optical readers, machines for transcribing data onto data media in coded form and machines for processing such data, not elsewhere specified or included	
	84718000	Other units of automatic data-processing machines
	84719000	Other
8517	Telephone sets, including telephones for cellular networks or for other wireless networks; other apparatus for the transmission or reception of voice, images or other data, including apparatus for communication in a wired or wireless network (such as a local or wide area network), other than transmission or reception apparatus of heading 8443, 8525, 8527 or 8528	
	85176200	Machines for the reception, conversion and transmission or regeneration of voice, images or other data, including switching and routing apparatus
8526	Radar apparatus, radio navigational aid apparatus and radio remote control apparatus	
	85269120	Radio navigational aid apparatus; Radio navigational receivers
	85269200	Radio remote control apparatus
8542	Electronic integrated circuits	
	85423111	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits; Goods specified in note 9(b)(3 and 4) to chapter 85; Multi-component integrated circuits (MCOs)
	85423119	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits; Goods specified in note 9(b)(3 and 4) to chapter 85; Other
	85423190	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits; Other
	85423911	Other; Goods specified in note 9(b)(3 and 4) to chapter 85; Multi-component integrated circuits (MCOs)
	85423919	Other; Goods specified in note 9(b)(3 and 4) to chapter 85; Other
	85423990	Other; Other
9032	Automatic regulating or controlling instruments and apparatus	
	90321020	Thermostats; Electronic
	90321080	Thermostats; Other
	90322000	Manostats
	90328100	Other instruments and apparatus; Hydraulic or pneumatic
	90328900	Other instruments and apparatus; Other

Notes: The reference CN classification is the 2017 version.
Source: Castellani et al. (2022).

Caselli and Coleman (2001) also argue that an alternative approach would be to exploit both production and trade data, so to account for both domestic and foreign sources of adoption of a technology. Such a measure would capture the net consumption (i.e., *production* + *import* – *export*) of a technology. In the case of the I4.0 technologies studied here, Castellani et al. (2022) highlight that the availability of production data is constrained by the actual presence of local producers across European countries. However, for producing countries, the authors also show that, import and net consumption measures are highly correlated, thus reassuring on our import-based measure being a good proxy of I4.0 technology adoption across European countries.

Potential multicollinearity concerns: Since ICT and some I4.0 technologies are quite close in nature (particularly, IIoT), one might be concerned about potential multicollinearity issues between our ICT capital stock variable and our I4.0 import stock variables. Similarly, another concern might arise to the extent to which capital goods used to compute our I4.0 variables are already accounted for in the ICT stock. To ease such potential concern, we highlight that the identification procedure we followed to create our IIoT variable (as well as the AIRs and the AM variables) using Comext CN 8-digit data should exclude such issue. Specifically, in order to avoid double counting with any ICT control variable, we specifically checked product categories capturing computing equipment as described by Caselli and Coleman (2001) and we excluded them from our selection of product categories for I4.0-related product categories (e.g., in the case of IIoT, we only focused on sensors, actuators, and all other IoT specific capital equipment). Still, we controlled for the potential presence of multicollinearity by computing variance inflation factors (VIF): these are never above the critical value of five for any of our I4.0-related variables.

Appendix C: Additional Tables

Table C1. Description of the variables

Variable Label	Variable Description
ΔlnA_{ijt}	Growth rate of total factor productivity (TFP)
ΔlnA_{Fjt}	Growth rate of total factor productivity (TFP) of the frontier country
$lnDTF_{ijt-1}$	1-year lagged distance from the technology frontier
RD_{ijt-1}	1-year lagged ratio between sectoral stock of R&D investments and sectoral value added
M_{ijt-1}	1-year lagged ratio between sectoral imports from the rest of the world and sectoral value added
ICT_{ijt-1}	1-year lagged ratio between sectoral stock of ICT investments and sectoral value added
$I40_{ijt-1}$	1-year lagged ratio between sectoral stock of I4.0 technology imports (AIRs + AM + IIoT) and sectoral value added
AIR_{ijt-1}	1-year lagged ratio between sectoral stock of advanced industrial robot imports (AIRs) and sectoral value added
AM_{ijt-1}	1-year lagged ratio between sectoral stock of additive manufacturing imports (AM) and sectoral value added
$IIoT_{ijt-1}$	1-year lagged ratio between sectoral stock of industrial internet of thing imports (IIoT) and sectoral value added

Notes: Data on aggregate imports comes from Eurostat's Comext data sets; data on sectoral variables comes from EU KLEMS, STAN, ANBERD and BTDIxE data sets.

Table C2. Econometric checks: productivity effects of I4.0 technology adoption

	System-GMM				LSDVC				FGLS			
ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔlnA_{Fjt}	0.025	0.032	0.037	0.028	0.028	0.029	0.032	0.029	0.007	0.010	0.012	0.008
	(0.066)	(0.066)	(0.034)	(0.066)	(0.020)	(0.020)	(0.020)	(0.020)	(0.009)	(0.009)	(0.009)	(0.009)
$lnDTF_{ijt-1}$	0.027**	0.010	0.010	0.016	0.219***	0.199***	0.208***	0.217***	0.021***	0.020***	0.015***	0.020***
	(0.011)	(0.012)	(0.010)	(0.010)	(0.023)	(0.023)	(0.023)	(0.024)	(0.003)	(0.003)	(0.003)	(0.003)
RD_{ijt-1}	0.617***	0.484***	0.505**	0.391***	1.266***	1.339***	1.311***	1.284***	0.403***	0.442***	0.422***	0.403***
	(0.170)	(0.168)	(0.173)	(0.145)	(0.153)	(0.148)	(0.150)	(0.151)	(0.043)	(0.045)	(0.043)	(0.043)
$(RD \times lnDTF)_{ijt-1}$	-0.555***	-0.452***	-0.487**	-0.337**	-1.193***	-1.256***	-1.222***	-1.208***	-0.382***	-0.413***	-0.395***	-0.380***
	(0.167)	(0.161)	(0.191)	(0.137)	(0.146)	(0.142)	(0.144)	(0.145)	(0.045)	(0.046)	(0.045)	(0.045)
M_{ijt-1}	-0.004***	-0.003***	-0.000	-0.004***	-0.009***	-0.011***	-0.008***	-0.009***	-0.003***	-0.003***	-0.002***	-0.003***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
$(M \times lnDTF)_{ijt-1}$	0.004***	0.003**	-0.001	0.004***	0.008***	0.009***	0.006***	0.007***	0.002***	0.002***	0.001**	0.002***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ICT_{ijt-1}	0.197*	0.103	-0.056	0.238**	0.495***	0.536***	0.354***	0.490***	0.146***	0.123***	0.066**	0.137***
	(0.118)	(0.066)	(0.065)	(0.106)	(0.080)	(0.078)	(0.068)	(0.072)	(0.035)	(0.032)	(0.027)	(0.035)
$(ICT \times lnDTF)_{ijt-1}$	-0.169	-0.038	0.142*	-0.221*	-0.535***	-0.591***	-0.447***	-0.533***	-0.128***	-0.096***	-0.043	-0.122***
	(0.148)	(0.080)	(0.067)	(0.132)	(0.089)	(0.086)	(0.082)	(0.083)	(0.038)	(0.032)	(0.028)	(0.038)
$I40_{ijt-1}$	0.153**				0.332***				0.100***			
	(0.065)				(0.047)				(0.023)			
$(I40 \times lnDTF)_{ijt-1}$	-0.137***				-0.307***				-0.073***			
	(0.051)				(0.056)				(0.020)			
AIR_{ijt-1}		0.310*				0.813***				0.342***		
		(0.175)				(0.148)				(0.101)		
$(AIR \times lnDTF)_{ijt-1}$		-0.323*				-0.665***				-0.307***		
		(0.175)				(0.152)				(0.091)		
AM_{ijt-1}			0.103***				0.577***				0.028	
			(0.022)				(0.092)				(0.049)	
$(AM \times lnDTF)_{ijt-1}$			-0.044**				-0.312***				-0.013	
			(0.017)				(0.053)				(0.030)	
$IIoT_{ijt-1}$				0.120**				0.245***				0.080***
				(0.051)				(0.043)				(0.019)
$(IIoT \times lnDTF)_{ijt-1}$				-0.095**				-0.196***				-0.058***
				(0.037)				(0.053)				(0.017)
TFP controls	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760
Groups	176	176	176	176	176	176	176	176	176	176	176	176
AR(1) test (*p*-value)	0.001	0.001	0.000	0.001								
AR(2) test (*p*-value)	0.326	0.286	0.437	0.313								
Hansen test (*p*-value)	0.704	0.606	0.681	0.691								

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator). Models (1) to (4) present estimates from System-GMM estimator: Hansen tests for overidentifying restrictions confirm the validity of instruments used (all regressors are assumed to be endogenous and instrumented with lags 1 and 2); AR(1) tests are rejected but AR(2) tests cannot be rejected. Models (5) to (8) present estimates from LSDVC estimator: bootstrapped standard errors (50 iterations) in parentheses (see Bruno, 2005). Models (9) to (12) present estimates from FGLS estimator: AR process is assumed to be panel-specific. TFP controls are h: hours worked; s: skill composition. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table C3. WLS-FE estimates: relationship between aggregate I4.0 technology adoption measures and TFP growth

ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ΔlnA_{Fjt}	0.257***	0.332***	0.040	0.040	0.354***	0.028	0.035	0.029	0.032	0.029	0.040
	(0.036)	(0.038)	(0.046)	(0.053)	(0.091)	(0.057)	(0.053)	(0.058)	(0.055)	(0.058)	(0.053)
$lnDTF_{ijt-1}$	0.244***	0.307***	0.246***	0.259***	0.358***	0.183***	0.237***	0.183***	0.221***	0.183***	0.258***
	(0.036)	(0.040)	(0.032)	(0.040)	(0.045)	(0.032)	(0.037)	(0.032)	(0.035)	(0.032)	(0.040)
RD_{ijt-1}	0.283***	0.248***	0.855***	1.168***	1.204***	1.239***	1.148***	1.251***	1.266***	1.262***	1.173***
	(0.071)	(0.064)	(0.153)	(0.224)	(0.195)	(0.245)	(0.227)	(0.243)	(0.228)	(0.242)	(0.226)
$(RD \times lnDTF)_{ijt-1}$	-0.969***	-0.816***	-0.793***	-1.046***	-1.122***	-1.164***	-1.041***	-1.176***	-1.159***	-1.185***	-1.051***
	(0.244)	(0.233)	(0.166)	(0.223)	(0.208)	(0.247)	(0.227)	(0.247)	(0.226)	(0.247)	(0.224)
M_{ijt-1}	-0.003***	-0.002***	-0.003***	-0.005***	-0.005***	-0.006***	-0.007***	-0.006***	-0.006***	-0.006***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$(M \times lnDTF)_{ijt-1}$	0.006***	0.006***	0.004***	0.006***	0.006***	0.007***	0.008***	0.007***	0.008***	0.007***	0.006***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ICT_{ijt-1}	0.196***	0.109**	0.060	0.183	0.180*	0.224	0.345**	0.256*	0.255**	0.256*	0.182
	(0.060)	(0.048)	(0.070)	(0.117)	(0.108)	(0.150)	(0.138)	(0.147)	(0.126)	(0.144)	(0.118)
$(ICT \times lnDTF)_{ijt-1}$	-0.384***	-0.171	-0.020	-0.209	-0.254	-0.280	-0.419**	-0.310	-0.327*	-0.314	-0.207
	(0.139)	(0.121)	(0.104)	(0.166)	(0.168)	(0.201)	(0.196)	(0.198)	(0.186)	(0.199)	(0.167)
$I40_{it-1}$	-0.001	0.093***	0.288***	0.370***	0.401***						
	(0.014)	(0.026)	(0.054)	(0.079)	(0.083)						
$(I40 \times lnDTF)_{ijt-1}$		-0.367***	-0.438***	-0.507***	-0.600***						
		(0.082)	(0.079)	(0.104)	(0.118)						
AIR_{it-1}						-0.038***	0.229***				
						(0.013)	(0.054)				
$(AIR \times lnDTF)_{ijt-1}$							-0.262***				
							(0.051)				
AM_{it-1}								-0.003	0.113***		
								(0.008)	(0.025)		
$(AM \times lnDTF)_{ijt-1}$									-0.155***		
									(0.032)		
$IIoT_{it-1}$										0.006	0.376***
										(0.019)	(0.082)
$(IIoT \times lnDTF)_{ijt-1}$											-0.511***
											(0.106)
TFP controls	-	-	s	h,s	h,s,2c	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,757	1,757	1,757	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760
R-squared (within)	0.422	0.457	0.376	0.359	0.409	0.289	0.353	0.285	0.323	0.285	0.357

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using value added shares in total economy as weights. TFP controls are h: hours worked; s: skill composition; 2c: two-country frontier. The dependent variable is the growth rate of TFP. ΔlnA_{Fjt} is the contemporaneous growth rate of TFP for the frontier; $lnDTF_{ijt-1}$ is the lagged distance from the technology frontier; RD_{ijt-1} is the lagged sectoral share of R&D stock in value added; M_{ijt-1} is lagged sectoral share of imports in value added; ICT_{ijt-1} is lagged sectoral share of ICT stock in value added; $I40_{it-1}$ is lagged country share of I4.0 technologies import stock in value added; AIR_{it-1} is lagged country share of advanced industrial robots import stock in value added; AM_{it-1} is lagged country share of additive manufacturing import stock in value added; $IIoT_{it-1}$ is lagged country share of industrial internet of things import stock in value added. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table C4. WLS-FE estimates: relationship between sectoral I4.0 adoption measures (computed using specific depreciation rates) and TFP growth

ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔlnA_{Fjt}	0.031	0.030	0.029	0.034	0.029	0.029	0.029	0.029
	(0.057)	(0.057)	(0.058)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
$lnDTF_{ijt-1}$	0.190***	0.202***	0.183***	0.202***	0.183***	0.225***	0.183***	0.225***
	(0.035)	(0.037)	(0.032)	(0.034)	(0.032)	(0.037)	(0.032)	(0.037)
RD_{ijt-1}	1.268***	1.323***	1.223***	1.229***	1.305***	1.231***	1.302***	1.233***
	(0.244)	(0.254)	(0.237)	(0.233)	(0.248)	(0.248)	(0.248)	(0.248)
$(RD \times lnDTF)_{ijt-1}$	-1.180***	-1.227***	-1.152***	-1.146***	-1.215***	-1.145***	-1.213***	-1.146***
	(0.249)	(0.256)	(0.241)	(0.234)	(0.252)	(0.253)	(0.252)	(0.253)
M_{ijt-1}	-0.008***	-0.011***	-0.005*	-0.008***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$(M \times lnDTF)_{ijt-1}$	0.007***	0.010***	0.005	0.005	0.008***	0.008***	0.008***	0.008***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ICT_{ijt-1}	0.426**	0.530**	0.209	0.365**	0.439*	0.470**	0.436*	0.468**
	(0.213)	(0.244)	(0.169)	(0.177)	(0.232)	(0.231)	(0.231)	(0.230)
$(ICT \times lnDTF)_{ijt-1}$	-0.474*	-0.581**	-0.265	-0.432*	-0.487*	-0.506*	-0.484*	-0.504*
	(0.263)	(0.294)	(0.220)	(0.234)	(0.283)	(0.276)	(0.282)	(0.276)
$drAIR_{ijt-1}$	0.225	0.685*						
	(0.138)	(0.371)						
$(drAIR \times lnDTF)_{ijt-1}$		-0.583						
		(0.373)						
$drAM_{ijt-1}$			0.015	0.496***				
			(0.023)	(0.165)				
$(drAM \times lnDTF)_{ijt-1}$				-0.257***				
				(0.087)				
$drIIoT_{ijt-1}$					0.100	0.463***		
					(0.072)	(0.138)		
$(drIIoT \times lnDTF)_{ijt-1}$						-0.466***		
						(0.127)		
$drIIoT^{0.315}_{ijt-1}$							0.117	0.555***
							(0.085)	(0.164)
$(drIIoT^{0.315} \times lnDTF)_{ijt-1}$								-0.561***
								(0.151)
TFP controls	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760
R-squared (within)	0.290	0.298	0.285	0.305	0.290	0.305	0.290	0.305

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using value added shares in total economy as weights. TFP controls are h: hours worked; s: skill composition. All variables are defined as in Table C1, but $drAIR_{it-1}$, $drAM_{it-1}$, $drIIoT_{it-1}$ and $drIIoT^{0.315}_{ijt-1}$, which are computed using sectoral- and capital-specific depreciation rates as discussed in Section 5.3. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table C5. WLS-FE estimates: relationship between sectoral I4.0 technology adoption measures and TFP growth using alternative measure from EU KLEMS

	1995-2019	1995-2008	2009-2019								
ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ΔlnA_{Fjt}	0.337***	0.416***	0.376***	0.349***	0.355***	0.308***	0.375***	0.361***	0.388***	0.350***	0.354***
	(0.089)	(0.096)	(0.059)	(0.069)	(0.069)	(0.073)	(0.069)	(0.061)	(0.063)	(0.069)	(0.070)
$lnDTF_{ijt-1}$	0.414***	0.538***	0.692***	0.719***	0.813***	0.709***	0.770***	0.590***	0.875***	0.719***	0.808***
	(0.068)	(0.094)	(0.160)	(0.168)	(0.164)	(0.144)	(0.151)	(0.169)	(0.189)	(0.169)	(0.164)
RD_{ijt-1}	0.900***	0.487***	0.704*	0.756**	0.654*	0.680*	0.633*	0.619	0.590	0.755**	0.652*
	(0.204)	(0.171)	(0.393)	(0.384)	(0.363)	(0.365)	(0.361)	(0.406)	(0.385)	(0.384)	(0.363)
$(RD \times lnDTF)_{ijt-1}$	-1.236***	-0.718***	-0.606	-0.776	-0.560	-0.697	-0.411	-0.229	-0.919	-0.770	-0.545
	(0.352)	(0.259)	(0.982)	(0.944)	(0.951)	(0.911)	(0.954)	(0.991)	(0.964)	(0.945)	(0.952)
M_{ijt-1}	0.022**	0.022**	0.018	0.017	0.016	0.019	0.018	0.013	0.006	0.017	0.016
	(0.009)	(0.009)	(0.016)	(0.015)	(0.012)	(0.015)	(0.014)	(0.015)	(0.012)	(0.015)	(0.012)
$(M \times lnDTF)_{ijt-1}$	-0.020*	-0.026***	-0.016	-0.014	-0.010	-0.017	-0.013	-0.008	0.002	-0.015	-0.010
	(0.010)	(0.009)	(0.028)	(0.028)	(0.021)	(0.028)	(0.024)	(0.026)	(0.022)	(0.028)	(0.021)
ICT_{ijt-1}	0.629***	-0.162	1.078***	0.998***	0.704*	0.998***	0.910**	1.070***	0.952***	1.000***	0.705*
	(0.197)	(0.178)	(0.412)	(0.375)	(0.363)	(0.379)	(0.388)	(0.383)	(0.368)	(0.377)	(0.363)
$(ICT \times lnDTF)_{ijt-1}$	-0.778**	0.270	-2.679***	-2.638***	-1.805**	-2.578***	-2.318**	-2.949***	-2.611***	-2.636***	-1.802**
	(0.315)	(0.243)	(0.933)	(0.889)	(0.871)	(0.887)	(0.911)	(0.911)	(0.873)	(0.890)	(0.869)
$I40_{ijt-1}$				0.042	0.341***						
				(0.073)	(0.122)						
$(I40 \times lnDTF)_{ijt-1}$					-1.070***						
					(0.351)						
AIR_{ijt-1}						-0.051	0.126*				
						(0.031)	(0.066)				
$(AIR \times lnDTF)_{ijt-1}$							-0.430**				
							(0.189)				
AM_{ijt-1}								0.104*	0.301***		
								(0.053)	(0.073)		
$(AM \times lnDTF)_{ijt-1}$									-0.396***		
									(0.111)		
$IIoT_{ijt-1}$										0.041	0.338***
										(0.073)	(0.123)
$(IIoT \times lnDTF)_{ijt-1}$											-1.089***
											(0.361)
Observations	3,827	2,227	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600
R-squared (within)	0.951	0.979	0.688	0.777	0.878	0.867	0.746	0.647	0.879	0.756	0.880

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using value added shares in total economy as weights. Data on TFP growth rate for manufacturing industries in Portugal are missing in EU KLEMS dataset. The dependent variable is the growth rate of TFP as taken from EU KLEMS data. All other variables are defined as in Table C1. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table C6. OLS-FE estimates: relationship between sectoral I4.0 technology adoption measures and TFP growth (unweighted)

ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔlnA_{Fjt}	0.029	0.029	0.032	0.030	0.029	0.033	0.029	0.030
	(0.061)	(0.061)	(0.061)	(0.061)	(0.062)	(0.061)	(0.061)	(0.061)
$lnDTF_{ijt-1}$	0.187***	0.227***	0.197***	0.206***	0.195***	0.215***	0.203***	0.224***
	(0.036)	(0.040)	(0.039)	(0.043)	(0.034)	(0.038)	(0.040)	(0.043)
RD_{ijt-1}	1.361***	1.274***	1.316***	1.354***	1.277***	1.320***	1.336***	1.294***
	(0.318)	(0.327)	(0.309)	(0.327)	(0.300)	(0.305)	(0.317)	(0.324)
$(RD \times lnDTF)_{ijt-1}$	-1.259***	-1.184***	-1.221***	-1.254***	-1.201***	-1.215***	-1.248***	-1.199***
	(0.309)	(0.314)	(0.305)	(0.319)	(0.296)	(0.293)	(0.309)	(0.314)
M_{ijt-1}	-0.009**	-0.010***	-0.009***	-0.011***	-0.005	-0.008**	-0.009***	-0.010***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
$(M \times lnDTF)_{ijt-1}$	0.008***	0.009***	0.007***	0.010***	0.004	0.007	0.008***	0.008***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
ICT_{ijt-1}	0.474*	0.507*	0.450*	0.553*	0.201	0.368*	0.477**	0.505**
	(0.276)	(0.272)	(0.250)	(0.285)	(0.200)	(0.205)	(0.225)	(0.226)
$(ICT \times lnDTF)_{ijt-1}$	-0.524	-0.544*	-0.499	-0.605*	-0.267	-0.459	-0.530*	-0.545*
	(0.336)	(0.323)	(0.308)	(0.342)	(0.257)	(0.281)	(0.289)	(0.282)
$I40_{ijt-1}$	0.087	0.338***						
	(0.060)	(0.127)						
$(I40 \times lnDTF)_{ijt-1}$		-0.319**						
		(0.126)						
AIR_{ijt-1}			0.282	0.829*				
			(0.190)	(0.441)				
$(AIR \times lnDTF)_{ijt-1}$				-0.700*				
				(0.396)				
AM_{ijt-1}					0.024	0.609***		
					(0.018)	(0.124)		
$(AM \times lnDTF)_{ijt-1}$						-0.328***		
						(0.071)		
$IIoT_{ijt-1}$							0.084**	0.254***
							(0.038)	(0.093)
$(IIoT \times lnDTF)_{ijt-1}$								-0.210**
								(0.087)
TFP controls	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760
R-squared (within)	0.232	0.246	0.232	0.239	0.228	0.251	0.236	0.244

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through OLS. TFP controls are h: hours worked; s: skill composition. All variables are defined as in Table C1. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table C7. WLS-FE estimates: relationship between sectoral I4.0 adoption measures and TFP growth (employment weighted)

ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔlnA_{Fjt}	0.030	0.030	0.033	0.031	0.031	0.035	0.030	0.031
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)
$lnDTF_{ijt-1}$	0.182***	0.222***	0.190***	0.201***	0.188***	0.209***	0.197***	0.218***
	(0.031)	(0.037)	(0.034)	(0.036)	(0.032)	(0.033)	(0.035)	(0.038)
RD_{ijt-1}	1.301***	1.218***	1.253***	1.306***	1.193***	1.243***	1.279***	1.239***
	(0.245)	(0.244)	(0.240)	(0.249)	(0.238)	(0.232)	(0.244)	(0.245)
$(RD \times lnDTF)_{ijt-1}$	-1.204***	-1.133***	-1.163***	-1.209***	-1.122***	-1.144***	-1.195***	-1.147***
	(0.248)	(0.249)	(0.245)	(0.251)	(0.241)	(0.232)	(0.248)	(0.250)
M_{ijt-1}	-0.009***	-0.009***	-0.008***	-0.011***	-0.004*	-0.008***	-0.009***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
$(M \times lnDTF)_{ijt-1}$	0.008***	0.008***	0.007***	0.010***	0.004	0.006**	0.008***	0.008***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
ICT_{ijt-1}	0.442*	0.473**	0.422**	0.523**	0.182	0.347**	0.453**	0.479**
	(0.227)	(0.226)	(0.209)	(0.240)	(0.160)	(0.166)	(0.189)	(0.192)
$(ICT \times lnDTF)_{ijt-1}$	-0.487*	-0.506*	-0.466*	-0.571**	-0.239	-0.430*	-0.501**	-0.514**
	(0.277)	(0.270)	(0.258)	(0.289)	(0.206)	(0.227)	(0.243)	(0.240)
$I40_{ijt-1}$	0.078	0.321***						
	(0.053)	(0.099)						
$(I40 \times lnDTF)_{ijt-1}$		-0.309***						
		(0.087)						
AIR_{ijt-1}			0.258*	0.760*				
			(0.156)	(0.416)				
$(AIR \times lnDTF)_{ijt-1}$				-0.636				
				(0.420)				
AM_{ijt-1}					0.024	0.587***		
					(0.017)	(0.192)		
$(AM \times lnDTF)_{ijt-1}$						-0.315***		
						(0.108)		
$IIoT_{ijt-1}$							0.079**	0.243***
							(0.034)	(0.074)
$(IIoT \times lnDTF)_{ijt-1}$								-0.204***
								(0.067)
TFP controls	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760
R-squared (within)	0.291	0.305	0.291	0.298	0.288	0.310	0.295	0.302

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using employment shares in total economy as weights. TFP controls are h: hours worked; s: skill composition. All variables are defined as in Table C1. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

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