Industry 4.0 and Productivity Growth: Evidence from European Countries

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Abstract

Do advanced manufacturing technologies boost TFP growth? This paper exploits whether the adoption of such '*game-changing*' technologies can positively affect the sectoral TFP growth rates across European countries, during 2009-2017. In so doing, we develop a proxy measuring the adoption of advanced manufacturing technologies following and improving the methodology proposed by previous seminal studies based on the idea that imports are a source of technology diffusion across countries. Our preliminary results suggest that determinants widely investigated in the empirical literature (e.g. R&D, international trade and ICT) seem to have a less significant contribution to productivity changes in the last decade, whereas new digital technologies (i.e. advanced industrial robotics, industrial internet of things and additive manufacturing) appear to bring substantial gains in TFP growth rates across manufacturing sectors, this is especially true in the case of relatively more technologically-advanced countries.

Keywords: Industry 4.0; advanced manufacturing technologies; technology diffusion; total factor productivity; industrial robotics; additive manufacturing; industrial internet of things.

1. Introduction

A 'technology shock', or a 'disruptive innovation', is the emergence of a new technology that can benefit some types of economic activities and substantially impact production ones. This may be the introduction of a new process or product that requires time to become mainstream, due to the need of accumulating new types of capital and to the resistance of the existing ecosystem towards change. Despite all periods of industrial upgrade in the past have witnessed at least one of these disruptive technologies, there is not universal agreement about what an industrial revolution is (Kagermann et al., 2013). From a technological perspective, four stages are identified: the first, with the introduction of water and steam-powered manufacturing facilities; the second, with the introduction of electrically powered technologies enabling the mass production; the third, with the introduction of Information and Communication Technology (ICT) in the manufacturing process. Recently, governments, industries and scholars have started to spend their attention on new digital (and *smart*) technologies as the key players for a new industrial revolution wave (Brynjolfsson and McAfee, 2014; Davies, 2015; Liao et al., 2017; OECD, 2017; WIPO, 2019; EIB, 2019).

This fourth industrial revolution, also known as industry 4.0 in manufacturing, bares new digital paradigms including a vast array of technologies. Advanced industrial robots (AIR), Internet of Things (IoT), additive manufacturing (AM), cloud computing, big data, artificial intelligence (AI), virtual and augmented reality open up for the creation of cyber-physical systems (CPSs) able to integrate seamlessly physical operations with digital insight (Lee, 2008; Rajkumar et al., 2010; Alcácer and Cruz-Machado, 2019), enabling the creation of smart factories (Lucke et al., 2008; Wang et al., 2016; Wang et al., 2016). Expansion of the product range, new opportunities for real-time customization and the acceleration of the entire product development cycle, together with the optimization of manufacturing operations thanks to predictive maintenance and other AI applications are only few of the gains coming from industry 4.0 technologies able to perform more flexibly, collaboratively and resiliently (Gorecky et al., 2014; Lee et al., 2014; Schuh et al., 2014; Lee et al., 2015; Kang et al., 2016; Stock and Seliger, 2016; Günther et al., 2017; Lee et al., 2018). Overall, the transformations brought by this fourth wave of industrialization are expected to lead to higher cost-efficiency and rise the productivity of firms (Kagermann et al., 2013; Schuh et al., 2014; Müller et al., 2018; Dachs et al., 2019), also benefitting market competition, employment overall, and contribute to GDP growth, particularly in advanced economies.

Chasing these goals of the fourth industrial revolution, several initiatives from national governments have taken place worldwide, such as 'Advanced Manufacturing Partnership' in the USA, the 'High-tech Strategy 2020' in Germany, the 'La Nouvelle France Industrielle' in France, the

‘Future of Manufacturing’ in the United Kingdom, ‘Industria 4.0’ in Italy, and the ‘Factories of the Future’ inside the European Programme Horizon 2020 (Liao et al., 2017; Mariani and Borghi, 2019).

In 2012, the OECD defined advanced manufacturing technologies as ‘*computer-controlled or micro-electronics-based equipment used in the design, manufacture or handling of a product*’ (OECD, 2012). This definition is rooted in the traditional applications of ICTs developed with the third industrial revolution started in the ‘50s and later become the mainstream industrial paradigm throughout the ‘70s and the ‘90s, which paved the way for today’s core technologies for industry 4.0. Among these technologies, we focus on three main embodied technologies bearing the highest potential for revolutionising the manufacturing landscape of advanced economies. These are advanced industrial robotics (AIR), industrial internet of things (IIoT) and additive manufacturing (AM), which the European Foundation for the Improvement of Living and Working Conditions (Eurofound) highlights as the ‘*game-changing*’ or disrupting technologies as they can find widespread application across every manufacturing industry due to their ‘*versatility and complementarity*’ (Eurofound, 2018: 9). These technologies are embodied technologies, thus to have adoption, a physical installation of such technologies is needed. The disruptiveness of these technologies resides not just in their power to affect products and their production processes, but also in the consequences they have for businesses and the working condition of their employees. For simplicity, hereafter we refer to this group of technologies as advanced manufacturing technologies (AMTs).

Yet, empirical evidence concerning these phenomena – mostly constrained to few technologies by the lack of extensive sources of information (Brynjolfsson et al., 2019a; Cockburn et al., 2019) –, along with a suitable measure of adoption allowing a deep investigation of the effects of such technologies on a large scale across countries and sectors in the long run, are still limited.

We try to fill this lack following the intuition by Caselli and Coleman (2001) and subsequent studies who looked at import data for disaggregated product categories to build proxies of cross-country adoption of computers, a well-established literature recognising international trade as one of the main sources of technology diffusion. In so doing, we propose a measure of adoption for AMTs, based on trade and production data, and we move forward this methodology adopting a structured approach for the identification of capital and intermediate goods specifically associated to AMTs leveraging on highly disaggregated data on 8-digit product codes, and excluding all non-relevant product categories.Thanks to these precise measures, we provide a first empirical evidence on the contribution of adopting a bundle of different industry 4.0 technologies to TFP growth. By looking at AIRs, IIoT and AM, and using a panel of 13 manufacturing industries across 14 European countries over the 2009-2017 period, we adopt a widely-used and robust empirical framework to analyse how these technologies affect productivity growth directly and by means of technology transfer from technological leaders.[1]

We find evidence of AMTs being relevant contributors to rates of TFP growth over the investigation period. When taken alone, each AMT has quantitatively and statistically important effects, either through direct mechanisms or *via* technological transfer from technological leaders. In particular, AIRs and AM seems to be more beneficial for technologically advanced countries, while economies more distant from the technological frontier luck of absorptive capacity to fully gain from their adoption. Conversely, IIoT appears to benefit TFP growth especially in countries on a catch-up trajectory. When we consider all AMTs jointly, we find robust evidence of the effects for AM and IIoT, while TFP growth gains from AIRs become weaker.

The rest of the paper is structured as follows. Section 2 briefly discusses the relevant literature on the topic, Section 3 highlights the empirical strategy which provides the background for the following empirical analysis. Section 4 discusses the data used. Section 5 presents and discusses the preliminary results of our econometric analysis. Finally, Section 6 concludes and outline future research.

2. Background

So far, industrial robots have been the main focus of empirical investigations looking at labor market mechanisms. Indeed, thanks to data from the International Federation of Robotics (IFR), few studies have investigated the occupational and wage effects of robotisation. Among these works, notable contributions are Acemoglu and Restrepo (2019), Chiacchio et al. (2018), Dauth et al. (2018) and Graetz and Michaels (2018). Few works also look at the effects of automation in general, industry 4.0 innovation and specific technologies on productivity growth measured in terms of total factor productivity (TFP), focusing on both adoption and production of these technologies. Even though preliminary evidence seems promising, the magnitude of the expected effect largely depends on the technology investigated, the data source and the estimation method. Much optimism relates to the coming role of AIs as engines of economic growth: several studies estimate the potential contribution to annual GDP growth in the next 10 to 15 years to range between 1.2 and above 4 percentage points, with long run estimates suggesting a rise of 14% of world’s GDP by 2030 (Purdy and Daugherty, 2016; Rao and Verweij, 2017; Bughin et al., 2018). At the same time, AI applications could bring labour productivity to rise by about 2% per annum in the long run (Purdy and Daugherty, 2016) with related improvements accounting for as much as 55% of global GDP increase by 2030 (Rao and Verweij,

[1] Important empirical contributions to this literature include Griffith et al. (2004), Cameron et al. (2005), Bourlès et al. (2013), Minniti and Venturini (2017) and Mason et al. (2020) at the industry level; Madsen et al. (2010) and Griffith et al. (2009) provide evidence at the macroeconomic and microeconomic level, respectively.

2017). Looking at other technologies, Manyika et al. (2015) forecast IoT applications will bring a contribute ranging between 4 and 11 percentage points of global GDP by 2025, while according to Purdy and Davarzani (2015) investments in industrial IoT could boost annual GDP growth by 1 to 1.5% by 2030. More generally, optimistic forecasts of different magnitude concern every technology related to the fourth industrial revolution, with overall industry 4.0 effects sizing around 24.3% of global GDP by 2025 (Huawei Technologies and Oxford Economics, 2017).

Though encouraging, these numbers remains forecasts bounded to assumptions on the future, and only few works so far have contributed towards the identification of the real economic contribution of industry 4.0 technologies. Notwithstanding, early econometric estimates seem to point in the same direction: Edquist et al. (2019) use early data available on licensed IoT connections to investigate the contribution that adopting IoT technologies have on country-level growth in TFP, highlighting that a 10% increase in the growth rate of IoT connections is associated with a 0.23% increase in the rate of growth of TFP and bringing to a potential contribution of 0.99% to annual GDP growth in the long run. Similarly, Graetz and Michaels (2018) attributes to the rising adoption of IR between 0.4 and 1% of the increase in labour productivity and between 0.3 and 0.8% of TFP growth, between 1993 and 2007. Looking at the creation of new knowledge and using patent data on industry 4.0-related innovations from the European Patent Office, Venturini (2019) estimates that latest technological developments of the fourth industrial revolution bring a positive and consistent contribution to TFP growth, accounting for 8% of cross-country observed change between the 90's and 2014. Despite this initial evidence, empirical work investigating the interplay between industry 4.0 and several different aspects of the economy has been widely penalised by the lack of data availability for most of technologies, especially when looking at their adoption.

Another point of discussion in the literature deals with the role that technologies embodied in the fourth industrial revolution might play in the long run. While there is more consensus on the advent of AI and AIRs as the new general purpose technologies (GPTs) – able to generate sustained economic growth by boosting continuous innovation and co-invention, spreading to every sector of the economy (Bresnahan and Trajtenberg, 1995; Carlaw and Lipsey, 2002) – both on theoretical (Trajtenberg, 2018; Aghion et al., 2019) and empirical ground (Brynjolfsson et al., 2019b), the potential role of many other industry 4.0 technologies as new GPTs is still largely debated. However, some evidence might indicate that other than few specific and highly promising technologies, it is also the whole interacting ecosystem created by the bundle of industry 4.0 technologies – realizing the yet mentioned CPSs – that is going to manifest its full role as the next GPT. Evidence from Venturini (2019) goes in this direction: according to author's estimates, it is the stock of innovations dealing with multiple industry 4.0 technologies that seems to generate productivity spillovers, which pattern conforms to the productivity *J-curve* – typically observed in the early stage of diffusion of new GPTs.

Despite the great deal of attention that industry 4.0 technologies have received from the academic world in the last decade, a clear picture of AMTs adoption and their actual effects is still a research area strongly under investigated. Most evidence currently comes either from surveys conducted in selected countries, case studies on a small number of firms, or from empirical works looking at specific technologies, limiting comparisons across countries and sectors, as well as across technologies. Thus, our aim is to fill this gap by suggesting a suitable proxy to measure the diffusion of AMTs and by providing evidence of the effects that multiple industry 4.0 technologies are having on industrialized countries, looking at their contribution to productivity growth across manufacturing sectors.

3. Empirical setting

3.1. Modelling technological catch-up

We start form the theoretical ground offered by models of endogenous innovation and growth (Romer, 1990; Aghion and Howitt, 1992, 1997; Acemoglu, 2009). Consider a world comprised of many countries denoted by $i = 1, \dots, I$ and manufacturing industries by $j = 1, \dots, J$ in which sectoral production at time t combines production factors according to a standard neoclassical production technology:

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

where Y denotes value added produced in each country and sector using labour L and physical 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 single production factor. Finally, A represents total factor productivity (TFP) as index of technical efficiency, allowed to vary across countries, industries and time; we denote the economy with the highest level of TFP at any time t in each sector j as the frontier, or technological leader ($i = F$).

Coherently with models of technological catch-up, TFP in sector j of country i is allowed to grow either directly, as a result of domestic progress, or indirectly through technology transfer from the technological leader for sector j:[3]

$$\Delta ln A_{ijt} = \alpha_{ij} + \beta_{ij} ln \left(\frac{A_F}{A_i}\right)_{jt-1} \tag{2}$$

[3] See, in particular, Bernard and Jones (1996) and Cameron et al. (2005) for a more complete derivation.

with $\alpha_{ij}, \beta_{ij} \geq 0$ corresponding to parameters capturing the rate of sector-specific innovation and the rate of technology transfer from the frontier, respectively. The rationale for equation (2) is that, for non-frontier countries the term $ln(A_F/A_i)_{jt-1}$ is positive and larger the further country i lies far from the frontier in sector j, and the greater the potential for productivity gains form technological transfer.

In the case of frontier countries instead, the sole source of productivity growth resides in domestic innovation, as in traditional endogenous growth models, such that the second term in the right-hand side of equation (2) is null. Considering equation (2) for both frontier and non-frontier countries and taking the first-order difference between the two we obtain equation (3), describing the evolution of a non-frontier country's distance relatively to the technological leader:

$$\Delta ln\left(\frac{A_i}{A_F}\right)_{jt} = \left(\alpha_{ij} - \alpha_{Fj}\right) + \beta_{ij} ln\left(\frac{A_F}{A_i}\right)_{jt-1}. \tag{3}$$

According to the model, in steady-state equilibrium, TFP in each sector j in all countries will grow at the same constant rate, such that TFP growth from domestic innovation and technology transfer in each non-frontier country equals TFP growth from domestic innovation alone for the technological leader. The model also allows all countries i 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 rate of TFP growth coming solely from domestic sources of innovation in that sector. Finally, each non-frontier country will be at an equilibrium distance behind the leader such that all countries feature the same TFP growth rate.

3.2. Adopting AMTs and TFP growth

Starting from the just described model and following the extensive theoretical and empirical literature on the sources of innovation, recognising the role of variables such as R&D, international trade, and other country and/or sectoral characteristics in determining both domestic innovation and fostering technological transfer by enhancing absorptive capacity,[4] we allow parameters α_{ij} and β_{ij} to be functions of R&D, international trade and investments in technologies such as ICT and AMTs:

$$\alpha_{ij} = \eta_{ij} + \gamma X_{ij}, \qquad \beta_{ij} = \delta + \theta X_{ij} \tag{4}$$

where X_{ij} is a vector including the determinants of changes in TFP growth rates highlighted above.

Substituting the equivalences in (4) into equation (3), we obtain:

$$\Delta lnA_{ijt} = \gamma X_{ijt-1} + \delta ln\left(\frac{A_F}{A_i}\right)_{jt-1} + \theta X_{ijt-1} ln\left(\frac{A_F}{A_i}\right)_{jt-1} + \vartheta \Delta lnA_{Fjt} + u_{ijt} \tag{5}$$

[4] See, for instance, Griliches (1979), Griliches and Lichtenberg (1984), Cohen and Levinthal (1989), Aghion and Howitt (1992), Coe and Helpman (1995) and Griffith et al. (2004) on the role of R&D; Coe et al. (1997), Frankel and Romer (1999), Keller (2000), Eaton and Kortum (2001) and Caselli and Wilson (2004) on the role of international trade; Krueger and Lindahl (2001) and Caselli and Coleman (2006) on the role of human capital.

where γX_{ijt-1} captures the direct effect of different sources of innovation on changes in productivity, the interaction term $\theta X_{ijt-1} ln(A_F/A_i)_{jt-1}$ captures the indirect effect acting through technology transfers from the technological frontier.[5] Equation (5) provides the starting point for our main econometric estimation: excluding the vector X of control variables, the equation can be thought as an equilibrium correction model (ECM) representation featuring a first-order autoregressive distributed lag model (ADL(1,1)) and describing the long run cointegrating relationship between a country's own TFP and technological leader's TFP:[6]

$$lnA_{ijt} = \lambda_1 lnA_{ijt-1} + \lambda_2 lnA_{Fjt} + \lambda_3 lnA_{Fjt-1} + u_{ijt}. \tag{6}$$

Assuming long run homogeneity ($\lambda_1 + \lambda_2 + \lambda_3 = 1$), this equation can be expressed as:

$$\Delta lnA_{ijt} = \lambda_2 \Delta lnA_{Fjt} + (1 - \lambda_1) ln\left(\frac{A_F}{A_i}\right)_{jt-1} + u_{ijt} \tag{7}$$

so that, ignoring control variables, equation (7) is identical to (5) with $1 - \lambda_1 = \delta$ and $\lambda_2 = \vartheta$.

The ECM representation above offers a straightforward interpretation: TFP growth in country i and industry j increases with TFP growth of the industry featuring as frontier (i.e. Fj) and with the distance of each country-sector pair from the frontier sector (Bourlès et al., 2013).

From an econometric stand point there may be different concerns with equation (5): first, unobserved heterogeneity arising from country-industry characteristics not captured by our explanatory variables, which affect rates of TFP growth and may be 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 industries showing higher intensities in investments in AMTs, R&D or trade patterns. For this reason, we use the within-groups estimator to control for unobserved heterogeneity correlated with our control variables, allowing the error term u_{ijt} to include country-industry fixed effects (η_{ij}). We further include time fixed effects (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. Hence, our final econometric specification becomes:[7]

$$\begin{aligned}\Delta lnA_{ijt} = \vartheta \Delta lnA_{Fjt} + \delta DTF_{ijt-1} + \gamma_1 X^{AMT}_{ijt-1} + \theta_1 X^{AMT}_{ijt-1} DTF_{ijt-1} \\ + \gamma_2 X^{CV}_{ijt-1} + \theta_2 X^{CV}_{ijt-1} DTF_{ijt-1} + \eta_{ij} + \tau_t + \varepsilon_{ijt}\end{aligned} \tag{8}$$

where DTF_{ijt} is the empirical counterpart of $ln(A_F/A_i)_{jt}$, X^{AMT} and X^{CV} are vectors including variables of AMTs adoption and control variables, respectively. Considering that the X^{AMT} vector

[5] In equation (5), the term η_{ij} is absorbed by the error term u_{ijt}.

[6] See Hendry (1996) for details.

[7] It should be noted that, though equation (8) features TFP growth rates as dependent variable it remains an equation expressed in levels and not in first difference, in which fixed effects introduced with the within-groups estimator are cancelled. This is a feature of the ADL(1,1) model behind the ECM (Bond et al., 2003; Bourlès et al., 2013).

only varies across countries, our specification allow these aggregate variables to have heterogeneous impacts across sectors. In (8), the equations for the frontier and for the non-frontier economies are stacked together, imposing cross-equation restrictions on all variables interacted with the distance from the technological leader for countries below the frontier.

Although the model we adopt in our empirical analysis is widely explored in the literature and represents the standard empirical framework for studies looking at determinants of TFP growth in a context of technological catch-up, there are still different issues with this empirical strategy, which relates to measurement error, endogeneity bias and the definition of the technological leader. For now, we leave these concerns to further development of this work. Another concern that may arise related to our analysis deals with the short time period investigated (2009-2017).[8] The choice of the period depends on the limited time series (and number of countries) for which data on AMTs – our main focus of investigation – are available. Furthermore, the year 2009 represents a meaningful starting point for our investigation on the role of AMTs as it was only after the global financial crisis that industry 4.0 technologies started receiving increasing attention in Europe (Kagermann et al., 2013). However, to increase comparability of our results with prior studies, we start the empirical analysis presenting specifications of equation (8) based on data covering a longer time period (1995-2017) and a larger pool of OECD countries, but exclude our main variables of interests (X^{AMT}). Results concerning all other variables included in these specifications are in line with prior empirical evidence in the literature on sources of TFP growth. Furthermore, all explanatory variables considered in both the main analysis on AMTs contribution to TFP growth rates and in the analysis on a longer time period present a behaviour which is qualitatively and statistically comparable, bringing cautious optimism on the goodness of our results.

4. Data and descriptive statistics

The data used for our empirical analysis comes from a variety of sources. As for our main variables of interest, investments in the three AMTs considered in this paper – AIRs, IIoT and AM –, we rely on country-level highly disaggregated trade and production data from Eurostat's Comext and Prodcom databases, thanks to the availability of fine-grained 8-digit product codes related to such technologies.

Drawing from Coleman and Caselli (2001), we create two main measures as proxy of adoption: (1) First, we measure AMTs adoption by imports of AMTs equipment and machineries, using

[8] In fact, the presence of the lagged dependent variable in the right-hand side of equation (8) implies that the within-groups estimator returns biased estimated coefficients for short time periods T, with such bias vanishing asymptotically in T (Nickell, 1981).

bilateral trade data at the finest level of disaggregated product class. We refer to this variable as adoption *via import.* The technology diffusion can be even stronger in those countries that do not have a well-developed national industry for such technologies, with no (or small) production, and no reported exports of related technologies as a consequence. So, as a further check, we restrict the sample to those countries that report imports but not exports of the identified product code. In this case, *import* is a pure measure of technology adoption. (2) Second, we measure AMTs adoption using the available information of production, based on the formula: *net consumption* = production + imports – exports. In so doing, we can account for both sources of capital good investments determining the adoption of a technology, namely domestic and foreign production, the latter through import flows. We refer to this variable as *net consumption.* The second measure should be more desirable. However, depending on the existing industrial structure of countries and on the availability of reliable data for a specific product codes, countries and years, that is not always the case. Indeed, the two measures reveal complementary aspects of AMTs adoption, but they also are highly correlated for most countries – especially where a local producing industry is not present or small, hence potentially considerable as comparable proxies. For these reasons, our main focus resides in the *import* variables, which allow greater comparability across countries, but we also control for the *net consumption* measure on restricted samples in order to provide additional evidence on the phenomenon under investigation.

The list of product codes following the respective classifications of Comext (i.e. the Combined Nomenclature) and Prodcom (i.e. the Classification of Products by Activity) matching our selection criteria, along with an extensive description of the three AMTs investigated in this paper, a detailed review of Comext and Prodcom data, and the data identification and validation process for the three AMTs are reported in Appendix[9].

We checked for changes occurred in each of the two classifications along the time period considered (2009-2017), then cross-checking the correspondence between the two classifications year-by-year in order to track any potential change related to the selected codes. In cases in which multiple CN codes correspond to one or more CPA codes or *vice versa*, as well as for cases in which the classification has changed over time, we followed the methodology by Van Beveren et al. (2012), creating *synthetic* codes grouping together the relevant codes. This procedure grants full consistency in the correspondence between trade and production data along time, and resulted in our product codes shrinking to 22 following the CN nomenclature, and 20 following the CPA nomenclature.

Starting from this data, we computed our *import* measure by creating one synthetic measure for each of the three AMTs as the sum of all product codes relating to the same technology, for each

[9] Due to space constraints, the Appendix is available upon request to the authors.

country and year of observation. In this way, we are able to identify for each European country in our panel a unique measure embodying all the imported goods related to each single technology. In the same way, we compute the second measure capturing *net consumption* as the sum of imports + production – exports (i.e. what Eurostat (2018) defines as '*apparent consumption*').

Though on a theoretical ground *net consumption* shows many attractive features for the purpose of our analysis, a cautionary note on its computation should be made. As outlined by Eurostat (2018), such measure may in some cases result to be negative. This is in fact not possible as a country's production data refers to sold production to both internal and external markets, thus theoretically accounting for exports as well. However, the characteristics of data clearly suggest that it is not always the case for this ideal match. Hence, in order to limit occurrences of such cases of *net consumption* < 0, while computing our second measure we only consider trade data associated to each product code, country and year showing a value of production > 0. Nonetheless, even performing this cautionary step, some negative instances still occur, further highlighting existing discrepancies in the way trade and production data are collected, as described above. As a result, we only consider country-year-technology observations for which the adoption measure results strictly positive. We test different proxy measures capturing AMTs adoption either based on the *import* and *net consumption* variables. Our preferred measure to capture the adoption of AMTs consists in the ratio between import flows for AIRs, IIoT and AM and investment flows in the reference type of capital for the three technologies (namely, machinery and equipment, IT, CT, and software and database capital investments).[10]

We use 2-digit sectoral data on value added, labour, aggregate capital, gross output, and investments in R&D and other types of capital and investments in R&D and other types of capital for European countries, United States (USA) and Japan from the 2019 release of EU KLEMS database. In addition, we also use comparable data for Canada, Korea and Norway from the latest release of the OECD Structural Analysis (STAN) database and Analytical Business Enterprise R&D (ANBERD) database. We combined this data with information on bilateral trade at the sectoral level coming from the OECD Bilateral Trade Database (BTDIxE). In particular, we use data on value added, labour and capital to compute TFP growth rates (our dependent variable ΔTFP_{ijt}, the empirical counterpart of ΔlnA_{ijt}) and to compute the relative TFP gap between frontier and non-frontier countries, the distance of each country i from the technological leader for each sector j (DTF_{ijt}, the empirical counterpart of $ln(A_F/A_i)_{jt}$). For this computation we use the superlative index approach

[10] Specifically, the AIRs adoption variable is computed as ratio between imports in AIRs and investments in machinery and equipment; the IIoT adoption variable is computed as ratio between IIoT imports and the sum of investments in IT, CT, and machinery and equipment; the AM adoption variable is computed as ratio between AM imports and investments in machinery and equipment. In addition, the ICT control variables is computed as ratio between computer imports and the sum of investments in IT, CT, and software and database.

by Caves et al. (1982a, b). The underlying production function assumed for its computation is translog, allowing form a more flexible specification of the production technology and outperforming other types of index assuming alternative production technology, such as Cobb-Douglas technologies, in terms of comparability (Griffith et al., 2004; Keller, 2004; Venturini, 2015). This established approach is widely used in the empirical literature involving measures of TFP growth.[11]

For other explanatory variables, we use data on sectoral R&D investments and sectoral bilateral trade to compute R&D intensity as the ratio between R&D investments and value added and import intensity as the ratio between imports from the technological leader to each non-frontier country and gross output. We also test less strict specifications in which technology transfer through imports is not restricted to the frontier alone, but is allowed to come from the rest of the world.

Our sample for the main investigation concerning AMTs contribution to TFP growth consists of 14 European countries[12] and 13 2-digit industries[13] over the period 2009-2017. We expand this sample in our preliminary analysis by including five additional countries (i.e. Canada, Japan, Korea, Norway and the USA) and expanding our time-series to the period 1995-2017 in order to provide further comparability with prior studies and tackle potential concerns on our results, as described in the previous section.

To illustrate magnitude of the phenomenon under investigation, in Figure 1, we graph the time trends of percentage growth rates of the *import* measure (left side), *net consumption* measure and production (right side) for the three AMTs, aggregated for all European countries included in our main analysis, using 2009 as reference year to index growth. We separate the different measures as they refer to different samples.[14] We also compare our AMTs measures with growth in benchmark categories to show the relative importance of the phenomenon as compared to trends for other '*mainstream*' goods.

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[11] For a complete derivation of how superlative index measures of ΔTFP_{ijt} and DTF_{ijt} are computed, see for example Keller (2002), Griffith et al. (2004), Cameron et al. (2005) and Griffith et al. (2009).

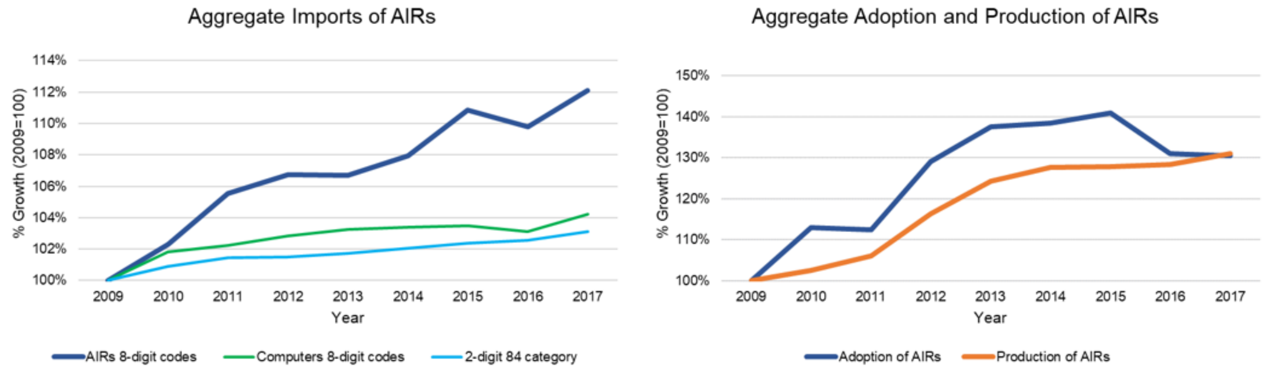
[12] Country list: Austria (AUT), Belgium (BEL), Czech Republic (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), United Kingdom (GBR), Italy (ITA), Netherland (NLD), Portugal (PRT), Slovak Republic (SVK), Sweden (SWE).

[13] Industry list (NACE rev.2): 1 - Food products, beverages and tobacco (C10_C12); 2 - Textiles, wearing apparel, leather and related products (C13_C15); 3 - Wood and paper products; printing and reproduction of recorded media (C16_C18); 4 - Coke and refined petroleum products (C19); 5 - Chemicals and chemical products (C20); 6 - Basic pharmaceutical products and pharmaceutical preparations (C21); 7 - Rubber and plastics products, and other non-metallic mineral products (C22_C23); 8 - Basic metals and fabricated metal products, except machinery and equipment (C24_C25); 9 - Computer, electronic and optical products (C26); 10 - Electrical equipment (C27); 11 - Machinery and equipment n.e.c. (C28); 12 - Transport equipment (C29_C30); 13 - Other manufacturing; repair and installation of machinery and equipment (C31_C33).

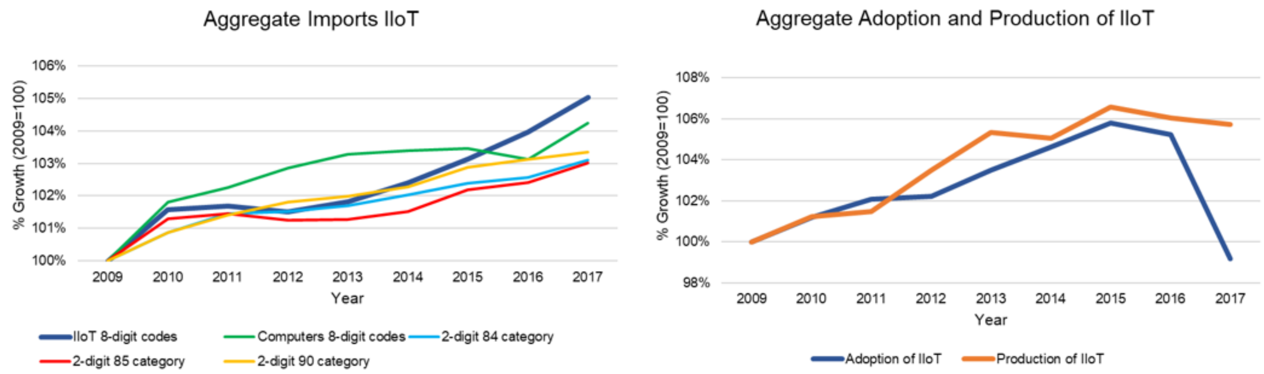
[14] As mentioned earlier in this section, our measures are computed as '*synthetic'* measures resulting from the aggregation of data for multiple product codes. In in the case of our adoption measures, these are computed only when production data are available, and that is not always the case depending on the presence of a domestic producing industry; this causing differences in the sample between the *import* and the *net consumption* variables.

Figure 1. Percentage Growth in AMTs' Imports, Adoption and Production, 2009-2017

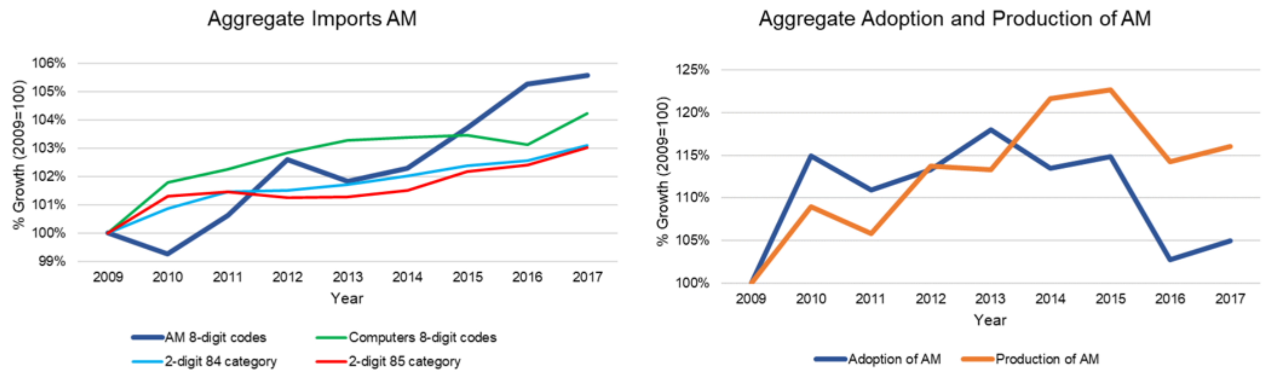
Panel A. Advanced Industrial Robots



Panel B. Industrial Internet of Things



Panel C. Additive Manufacturing



Notes: Authors' own computations based on Comext and Prodcom data. Original data have been corrected for PPPs and expressed as shares of thousands people employed to increase comparability over time and filter out cross-country differences in magnitude.

Figure 1 highlight a faster growth of AMTs when we compare them to benchmark categories (i.e. data on 8-digit product codes for computers, and 2-digit aggregated product classes to which the select 8-digit codes for AMTs belong). In particular, the left side figure in Panel A shows imports of AIRs have risen by around 12% between 2009 and 2017, between 8 and 9% more than benchmark categories. Similarly, but with a less strong growth, also IIoT and AM measures (left side of Panel B and C, respectively) have both risen by around 6% over the observation period, outperforming the growth of the respective benchmarks. Specifically, the two AMTs have both grown around 1% more than computer imports and around 3% more than 2-digit categories. Overall, all three AMTs shows strong growth over the observation period, especially when put in relation to relevant counterfactuals, stimulating much interest over their growing diffusion. When looking at AMTs in relation to one another, we believe the slower growth observed for IIoT and AM relative to AIRs depends on differences in the stage of maturity of the technologies: while IIoT implement technologies, hence capital goods, now well established and mature (Gubbi et al., 2013; Sethi and Sarangi, 2017), AM is a relatively young technology in terms of its diffusion, still undergoing a strong innovation (Attaran, 2017). Looking at adoption and production patterns (right side of Figure 1), Panel A confirms the strong diffusion of AIRs across European countries in our sample, showing a 30% growth in both measures, with adoption peaking at around 40% between 2013 and 2015. Adoption and production of IIoT (Panel B) present a similar pattern, with an increase similar to that of their imports, at around 6%; however, Figure 1 shows a steep drop in adoption for IIoT in 2017, not paired by a drop in production, probably highlighting the inconsistencies in the source data described above. Finally, similar issues persist for AM: Panel C shows both adoption and production to increase between 2009 and 2017, with the former rising by around 15% for most years then dropping similarly to IIoT at the end of the period, and the latter showing an overall percentage growth of around 15% in 2017 and peaks of 23% in previous years.

5. Results

5.1. TFP growth and technology transfer in latest decades

Before turning our attention to the contribution of AMTs to TFP growth, leveraging on the longer period and larger pool of OECD countries in our panel dataset, we first provide evidence on the role of technology transfer and other determinants of TFP growth (namely, R&D investments and international trade) between late 90's and latest years. As already described above, this preliminary exercise allows us to provide comparable estimates to prior studies, as well as providing initial results for our control variables, both on a longer and on a shorter period. In this regard, our aim is to show consistency between the estimated coefficients when we bring the sample down to only European countries included in the main analysis, and to the 2009-2017 period.

Column (1) of Table 1 shows estimates of equation (8) on the full sample available for our analysis, looking at the role of technology transfer, R&D and international trade – measured by import intensity from the frontier – in determining TFP growth. All three coefficients enter positively in the specification, suggesting a positive contribution of each measure to rates of TFP growth. The DTF and the R/Y terms are also statistically significant at the 1% level, overall confirming prior findings in the empirical literature. In columns (2) and (3), we augment the initial specification by including the leader's contemporaneous TFP growth, and the interaction terms between measures of R&D and import intensity and the DTF, respectively. In column (2), the role of contemporaneous TFP growth rates for the frontier country is positive and statistically significant at the 1% level and imply just small changes in the coefficient of the other explanatories. The specification in column (3) also control for interaction terms: while ΔTFP_F and DTF terms remain virtually unchanged in both magnitude and statistical significance, when including its interaction term with technology transfer, the coefficient of the linear relationship between TFP growth and R&D intensity drops by half and remains significant at the 5% level. As found in prior evidence on the contribution of these variables to TFP growth,[15] the interaction term with R&D is positive and statistically significant, meaning that the larger the technological gap between frontier and non-frontier countries, the higher the potential for technology transfer *via* R&D and the higher the contribution to non-frontier TFP growth. Both the linear and the interacted coefficients for the import variable remain not statistically significant, though the magnitude of the coefficient capturing the linear relationship largely increases when including its interaction with the DTF. A large body of literature stresses the role of international trade in cross-country growth and technological catch-up acting, for example, through spillovers (Eaton and Kortum, 2001; Caselli and Wilson, 2004; Acharya and Keller, 2009) and market expansion resulting from imported inputs (Colantone and Crinò, 2014; Castellani and Fassio, 2019). However, most studies on productivity growth focuses on the 70's to 90's period, witnessing overall different international trade trends – mostly characterized by increasing trade openness – compared to those seen in latest years, nonetheless finding only weak evidence on the role of imports (Griffith et al., 2004). Our results concerning the role of international trade in determining rates of TFP growth are not surprising when seen under this light.

Columns (4) and (5) present estimates when we constrain the sample to European countries alone. Results remain virtually unchanged both qualitatively and statistically when we compare column (4) with column (2), whereas in column (5) the coefficient for R&D intensity lose statistical significance. Overall, the sample restriction does not seem to bring any particular bias in our results.

We further move towards our main specifications with columns (6) and (7), where we limit the analysis to the final sample period 2009-2017. Also here, results remain widely unchanged: in both columns we observe a steep increase in the coefficient for the frontier's contemporaneous TFP growth (ΔTFP_F), which doubles as compared to previous specifications, while in the last specification in column (7) both terms (linear and interacted) involving R&D intensity lose statistical significance. Although the role of R&D is emphasized in both the theoretical and the empirical literature, other

[15] See, for instance, Griffith et al. (2004) and Cameron et al. (2005).

empirical works find similar evidence on the statistical significance of R&D variables, even when looking at longer periods T (e.g. Minniti and Venturini, 2017).

Table 1. Impact of Technology Transfer, R&D and International Trade on TFP Growth

ΔTFP_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔTFP_{Fjt}		0.351***	0.346***	0.452***	0.415***	0.819***	0.846***
		(0.074)	(0.073)	(0.085)	(0.095)	(0.065)	(0.056)
DTF_{ijt-1}	0.241***	0.282***	0.282***	0.284***	0.307***	0.391***	0.393***
	(0.063)	(0.064)	(0.065)	(0.082)	(0.084)	(0.101)	(0.102)
R/Y_{ijt-1}	0.818***	0.768***	0.371**	0.778***	0.320	0.984***	0.851
	(0.171)	(0.159)	(0.184)	(0.170)	(0.215)	(0.255)	(0.970)
$(DTF * R/Y)_{ijt-1}$			0.076***		0.079**		0.017
			(0.028)		(0.032)		(0.127)
M_{ijt-1}	0.073	0.061	0.666	-0.051	1.090	0.312	-0.152
	(0.179)	(0.191)	(0.422)	(0.236)	(0.820)	(0.300)	(0.437)
$(DTF * M)_{ijt-1}$			-1.126		-1.775		0.715
			(1.049)		(1.553)		(0.583)
Sample		OECD		Europe		Europe	
Period		1996-2017		1996-2017		2009-2017	
Observations	5,061	5,061	5,061	3,858	3,858	1,395	1,395
Adjusted R-squared	0.526	0.856	0.706	0.491	0.755	0.823	0.950
Country-Sector Pairs	232	232	232	176	176	176	176
Average N of Years	22	22	22	22	22	8	8
Country-Sector FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses. Observations are weighted using sectoral shares of total manufacturing employment. The dependent variable is the growth rate of TFP. ΔTFP_{Fjt} is the contemporaneous growth rate of TFP for the frontier; DTF_{ijt-1} is the lagged distance from the technology frontier; R/Y_{ijt-1} is the lagged R&D intensity; M_{ijt-1} is lagged import intensity. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

5.2. Main results on AMTs

We now turn to our main focus of research on the role of AMTs' adoption in contributing to cross-country TFP growth, between 2009 and 2017. As discussed in section 4, we measure the AMT adoption via *import* data for each technology, computed as the ratio between sum of import flows in all product codes relating to that technology and the investment flows in the reference type of capital for the three technologies. Our starting point is the specification in column (7) of Table 1, which we now augment including direct and moderated measures of adoption for AIRs, IIoT and AM.. While we expect direct relationships for all three AMTs to be positive, we have no prior expectation on the sign of the interacted terms. In fact, the diffusion of AMTs, and industry 4.0 technologies in general, is mostly concentrated in more developed countries, which are closer to the technology frontier; hence, the sign of the interacted term will depend on each country-sectors ability to capture the moderated benefits of these new digital technologies, and this will depend on their *absorptive capacity*.

Column (1) in Table 2 examines the role of directly adopting AIRs: the coefficient enters positively and is significant at the 5% level, suggesting that a 0.001 percentage point increase in the adoption of AIRs results in just below 0.01 percentage point rise in rates of cross-country TFP growth. In order to control for other sources of productivity growth coming from other technologies – ICT, in particular, we control for computers' adoption: the coefficient of the variable is negative, small in magnitude and statistically significant at the 5% level, suggesting a weakly negative contribution to TFP growth from adopting purely '*traditional*' forms of ICT in latest years. This result is in line with latest evidence on the relationship between '*mainstream*' measures of ICT investments and productivity growth (Edquist and Henrekson, 2017). Once we include these technology variables, coefficients for all other variables included in column (7) of Table 1 remain qualitatively unchanged. In column (2), we consider both the level of AIRs adoption and its interaction with the DTF term. The linear term for the AMT increases in magnitude, but statistical significance becomes weaker, while the interaction term enters negatively and is not significant. The latter result suggests that countries lagging behind technological leaders might still lack enough *absorptive capacity* to capture the benefits of these new digital technologies, moderated through technology transfer. In particular, relative lack of proper infrastructure and widespread uptake of traditional forms of ICT, together with mismatch in the type of skills required by the labour force may result in the inability to translate the adoption of AIRs in productivity gains. As for the control variable on computers' adoption, when including also its interaction with the DTF, both variables suggest close to 0 and not significant contribution to TFP growth deriving from ICT.

Columns (3) and (4) repeat the analysis but looking at AM. The direct effect of AM adoption on rates of TFP growth seem to be positive in column (3), statistically significant at the 5% level and implying that 0.01 percentage point increase in AM adoption brings around 0.07 percentage point increase in TFP growth across countries. When we include also the interaction with the distance from the frontier, the linear term remains significant and increases in magnitude, while the interacted term is only weakly significant (at the 10% level) and enters the specification negatively. While main findings for the computers control variable and all other determinats of TFP growth are qualitatively unchanged from the specifications in columns (1) and (2), our results point at AM technology bringing significant contributions to productivity mostly for countries close to the technology frontier. At the same time, technological laggards who adopt AM technologies seems to lack underlying conditions to allow them to capture productivity spillovers from this AMT and catch-up with the frontier.

We look at the relationship between IIoT technologies adoption and TFP growth rates in columns (5) and (6). When IIoT enters the model only through its direct effect (column (5)), our estimates hint at an overall positive contribution to cross-country productivity growth: the coefficient is statistically significant at the 1% level and suggest a 0.1 percentage point increase in IIoT adoption to bring about 0.015 percentage point rise in rates of TFP growth. When we introduce also the interacted term capturing gains through technology transfer from the frontier, the coefficient of the linear term turns negative, maintaining statistical relevance, whereas the interacted term is positive and statistically significant at the 1% level. This behaviour suggests that, once we distinguish for differentiated effects,

Table 2. Impact of AMTs on TFP Growth

ΔTFP_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔTFP_{Fjt}	0.689***	0.798***	0.831***	0.859***	0.857***	0.825***	0.785***
	(0.083)	(0.078)	(0.063)	(0.103)	(0.052)	(0.125)	(0.116)
DTF_{ijt-1}	0.451***	0.551***	0.424***	0.597***	0.500***	0.365***	0.475***
	(0.080)	(0.104)	(0.090)	(0.102)	(0.105)	(0.093)	(0.109)
R/Y_{ijt-1}	-0.122	-0.290	0.098	0.124	0.025	0.679	0.416
	(0.714)	(0.905)	(0.766)	(0.720)	(0.930)	(0.809)	(0.589)
$(DTF * R/Y)_{ijt-1}$	0.141	0.156	0.115	0.104	0.112	0.035	0.078
	(0.095)	(0.121)	(0.100)	(0.098)	(0.123)	(0.112)	(0.084)
M_{ijt-1}	0.088	-0.076	-0.238	-0.163	-0.061	-0.049	-0.066
	(0.366)	(0.332)	(0.391)	(0.255)	(0.407)	(0.255)	(0.222)
$(DTF * M)_{ijt-1}$	0.427	0.517	0.651	0.413	0.546	0.293	0.297
	(0.482)	(0.479)	(0.490)	(0.393)	(0.527)	(0.389)	(0.360)
AIR_{ijt-1}	9.858**	14.374*					6.863
	(4.078)	(7.923)					(5.545)
$(DTF * AIR)_{ijt-1}$		-7.215					-6.056
		(6.006)					(4.615)
AM_{ijt-1}			7.120**	15.088**			11.163*
			(3.197)	(7.145)			(5.794)
$(DTF * AM)_{ijt-1}$				-10.616*			-8.960*
				(6.019)			(5.122)
$IIoT_{ijt-1}$					0.151**	-0.166**	-0.209***
					(0.068)	(0.068)	(0.060)
$(DTF * IIoT)_{ijt-1}$						0.323***	0.327***
						(0.075)	(0.071)
PC_{ijt-1}	-0.014**	-0.004	-0.010**	0.000	-0.014***	0.034**	0.019
	(0.007)	(0.031)	(0.005)	(0.015)	(0.005)	(0.017)	(0.015)
$(DTF * PC)_{ijt-1}$		-0.009		-0.008		-0.036***	-0.021*
		(0.025)		(0.013)		(0.014)	(0.013)
Observations	1,395	1,395	1,395	1,395	1,395	1,395	1,395
Adjusted R-squared	0.851	0.938	0.863	0.710	0.989	0.872	0.603
Country-Sector Pairs	176	176	176	176	176	176	176
Average N of Years	8	8	8	8	8	8	8
Country-Sector FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Notes: Sample period is 2009-2017. Robust standard errors in parentheses. Observations are weighted using sectoral shares of total manufacturing employment. The dependent variable is the growth rate of TFP. ΔTFP_{Fjt} is the contemporaneous growth rate of TFP for the frontier; DTF_{ijt-1} is the lagged distance from the technology frontier; R/Y_{ijt-1} is the lagged R&D intensity; M_{ijt-1} is lagged import intensity; AIR_{ijt-1} is lagged adoption of advanced industrial robots; AM_{ijt-1} is lagged adoption of additive manufacturing; $IIoT_{ijt-1}$ is lagged adoption of industrial internet of things. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

countries with a close-to-zero technology gap – hence, those closer to the frontier – who adopt IIoT are not bettered-off in terms of TFP growth. On the other hand, countries on a catching-up trajectory are better able to harness productivity spillovers through technology transfer from more advanced countries. As for other determinants of TFP growth in these two specifications, the overall behaviour of other explanatories remains similar to that observed in the specifications seen for AIRs and AM, while in the case of the computers control both magnitude and statistical significance increases when the main focus is on IIoT.

Finally, in column (7) we analyse the simultaneous impact of all three AMTs allowing them to affect TFP growth, both through direct and moderated effects. The qualitative behaviour of all three AMTs is coherent with that observed in the previous specifications: signs and magnitude of the coefficients for both linear and interacted terms are comparable, but our findings suggest that some AMTs are more beneficial than others. In particular, both coefficients for the AIRs variables are smaller and not statistically significant anymore; similarly, jointly considering different industry 4.0 technologies highlights only weak evidence on the real contribution to TFP growth rates brought by AM, as in column (7) both the linear and interacted terms are only significant at the 1% level. Finally, the most robust evidence we find relates to productivity spillovers from IIoT adoption, with both the related variables showing a small increase in the magnitude of the coefficients and robust statistical significance.[16]

6. Conclusions

This paper makes a first attempt to investigate the relationship between a subset of industry 4.0 technologies we refer to as advanced manufacturing technologies (AMTs), bearing a high disruptive potential for manufacturing activities, and cross-country productivity growth. We refer to advanced industrial robots (AIRs), industrial internet of things (IIoT) and additive manufacturing (AM) as the main '*game-changing*' technologies and we analyse how their adoption has affected within-industry TFP growth rates in a panel of 14 European countries in the last decade. Following a well-established literature, we test proxies of adoption based on trade (and also production) data, although we enrich this approach by identifying fine-grained 8-digit product codes of capital and intermediate goods

[16] We also test all our results using alternative measures for the role of international trade and AMTs adoption. Specifically, we use a more flexible definition of imports intensity in which the source of imports is not constrained to the frontier economy, but is the rest of the world. As for AMTs adoption measures, we test variables built expressing AMTs imports as share of each country's manufacturing gross output. We also test pure measures of AMTs imports expressed in log, while also controlling for country size through the inclusion of manufacturing gross output (also expressed in log). Estimates for these robustness checks are in line with our preferred results reported here.

strictly related to AMTs. Our methodology allows the highest precision in the identification of such product codes, removing potential noise brought by all unrelated product codes otherwise considered when looking at more aggregated trade data. The resulting adoption measures for AMTs enables us to study the diffusion of new technologies when actual adoption data are not publicly available yet. We apply such measures to a largely used and robust empirical framework, contributing to the literature on the determinats of TFP growth and technological convergence.

We find that, while other determinants widely investigated in the empirical literature (R&D, international trade and ICT) seem to have had a less significant contribution to changes in productivity, other new digital technologies now appear to bring substantial gains in TFP growth. Differently from prior findings on, for instance, R&D though, AMTs adoption affects productivity differently, depending on each country proximity to the technological frontier. While AIRs and AM seem to affect productivity growth rates mainly through direct channels, meaning that more technologically advanced countries are best positioned to gain from these technologies, our results suggest an opposite scenario when it comes to IIoT. These diverging findings can only be explained looking at contextual conditions, as for technological laggards in our sample local characteristics influencing their absorptive capacity (e.g. knowledge, infrastructures, skills, policy incentives, etc.) either hinders or boosts technology transfer from the frontier depending on the specific industry 4.0 technology considered. From a quantitative stand point, our findings on AIRs and IIoT are in line with and add to the existing evidence (Graetz and Michaels, 2018; Edquist et al., 2019). Concerning AM, there is little evidence on its relationship with productivity measures, and this is the first attempt of quantifying AM contributions to TFP growth. However, existing evidence seems to point in the direction of AM bringing some productivity gains in some specific industries (Felice et al., forthcoming).[17]

Our analysis is not free from shortcomings, especially from an econometrical standpoint. We leave treating concerns related to alternative measures of TFP growth accounting for changes in hours worked, definition of the frontier economy, measurement error and endogeneity bias to further development of this work.

As mentioned above, further research in this area might investigate the role of different contextual conditions in explaining why some technologies benefits technological laggards more than others. In particular, following the wave of industry 4.0 initiatives introduced by virtually every European country during latest years, targeted policies resulting in incentives being channelled more towards

[17] In their work, the authors find that the diffusion of AM technology, as measured by sectoral patenting activity, relates significantly with levels of labour productivity in industries characterised by high product customisation intensity; however, the technology seems to impact economic activities at other levels, for example through labour market mechanisms.

some industry 4.0 technologies than others might have a role in explaining the differences documented here.

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