# Firm-level productivity and profitability effects of managerial and organisational capabilities and innovations

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## Abstract

Using data for a large sample of European firms, the present work investigates the productivity effects associated with the generation of the technologies related to the Fourth Industrial Revolution (4IR) and with managerial and organisational capabilities (MOCs) related to the adoption of new managerial practices, such as the ISO 9001 certification. By adopting a distance to frontier framework (DTF), in the first part of the study, we find that companies innovating in the fields of 4IR (mainly Artificial Intelligence) have a significantly faster productivity growth and this is proportional to how far they lie behind the frontier. In the second part, we investigate whether new managerial practices help falling-behind companies fill the gap with firms with the highest levels of productivity, profitability and average wages paid in Italy. We find that the ISO 9001 certification helps firms below the frontier to partially recover the gap in terms of multifactor productivity (MFP) and profits.


*Keywords:* Multifactor productivity, Fourth Industrial Revolution technologies, Artificial Intelligence, managerial capabilities, ISO 9001 certification.

# Firm-level productivity and profitability effects of managerial and organisational capabilities and innovations

## 1. Introduction

In a world of great transformations, diverging productivity performance and widening income disparities (Berlingieri *et al.,* 2017), it is crucial to know which factors promote economic change and which ones accommodate it within an intangible economy (Haskel & Westlake, 2017).

A pronounced stagnation process, characterised by diminishing rates of productivity growth, is shared by an increasingly larger number of economies. This trend is ascribed to various factors, but a key role is argued to be played by the difficulty of the mass of the firms to improve their productivity levels and cope with the performance of the most successful companies. A diverging process between frontier and laggard firms is common to most countries and industries but appears to be particularly strong in such sectors as Information and Communication Technologies (ICT) services that, recently, have been affected by a vertiginously rapid technological change (Andrews *et al.,* 2019).

The advent of the Fourth Industrial Revolution (4IR) may reinforce this long-lasting trend and exacerbate its economic effects. Nonetheless, as in all breakthrough transformations of the past, the arrival of a new generation of technologies, known as General Purpose Technologies - GPT (Bresnahan & Trajtenberg, 1995; Brynjolfsson *et al.,* 2019), may offer unforeseen opportunities for changing business configuration, improve firm performance and, on aggregate, revert the downward trend of productivity (Mokyr, 2018).

The present work investigates across a large sample of European firms the productivity effects associated with: (i) the generation of the latest family of technologies, i.e. innovations in technological fields related to the 4IR; (ii) the managerial and organisational capabilities (MOCs)[1] related to the adoption of new managerial practices, such as the ISO 9001 certification. Due to data limitations, this second aspect has been investigated only for Italian companies, hence the second part of the study concentrates on a single-country analysis.

Some pioneering studies have documented that companies innovating in the new technological areas experience a larger expansion of sales, employment and even productivity growth,

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[1] Henceforth, to avoid repetitions, we use interchangeably the terms MOCs, managerial practices and quality improvement methods.

as they can exploit the rising demand of new products and significant efficiency gains associated with new input configurations and organisational change. However, it is also documented that productivity gains are increasingly induced by softer forms of innovation and investment in intangibles, such as those associated with new managerial practices. For instance, quality certifications would increase firm compliance to standardised procedures, facilitate the accumulation of codified knowledge and favour the exploitation of best organisational practices.

Based on these premises, the present work adopts a distance to frontier framework (DTF) to estimate whether European firms innovating in the 4IR tech fields denote a faster productivity track and how these productivity gains show up. We find that Artificial Intelligence (AI) innovating companies, in particular, have a significantly faster productivity growth and this is proportional to how far they lie behind the productivity frontier. In other words, the generation of AI technologies seems to create opportunities for these firms to close the gap and catch up the productivity leader. In the second part of the work, we investigate whether new managerial practices help falling-behind companies fill the gap with firms with the highest levels of productivity, profitability and labour compensation in Italy. We find that ISO 9001 certification helps firms below the frontier to partially recover the gap in terms of multifactor productivity (MFP) with respect to the top 5% Italian companies. This gain also reflects on higher profits for the laggards.

The outline of the paper is as follows. Section 2 surveys the most recent literature on technological and managerial drivers of productivity performance at firm level. Section 3 lays down both the analytical framework, based on the distance to frontier approach, and the econometric methodology, based on Difference-in-Difference regression, used to identify the productivity impact of the intangible assets under the scrutiny. Section 4 presents the data on the large sample of European and Italian firms covered by the present analysis, reporting a small set of summary statistics. Estimates on the productivity effect of 4IR technologies, obtained using a panel sample of firms from sixteen European countries, are presented Section 5. Next, estimates on the performance impact of quality improvement methods pursued by Italian companies are presented in Section 6. Finally, Section 7 concludes.

## 2. Literature review

The set of technologies rooting the 4IR is rapidly expanding but, overall, includes the following categories: Artificial Intelligence (AI), additive manufacturing (3D), Internet-of-Things (IoT) and robotics (EPO, 2017; WIPO, 2019). These technologies are based on large-scale digitised information, massive computing capabilities and intelligent software systems. They are embodied in an increasingly number of machines that, thanks to these components, can easily adapt to the changing productive environment (Schawb, 2016).

From an economic perspective, the new generation of innovations is considered as GPT (Trajtenberg, 2018; Craft, 2021) and hence are expected to yield positive productivity effects with lags (*productivity J-curve*; Brynjoflsson *et al*, 2021). Optimistic previsions on the wide productivity growth effects expected from AI and other disruptive technologies (Nordhaus, 2020) contrast to more conservative views contending that these innovations would be evolutionary rather than revolutionary technologies, as they would favour the implementation of old tasks in new ways and would not be as pervasive as often argued (Gordon, 2016; Vannucini & Prytkova, 2021).

While descriptive evidence on the diffusion of these technologies is growing fast (EPO, 2017; UK IPO, 2019; Barrufaldi *et al.,* 2020), econometric evidence on productivity effects of the new technologies is still scarce. At the economy level, Venturini (2022) illustrates that the development of 4IR technologies, taken as a whole, has produced an economically small but a highly significant spill over effect on productivity levels, that can be quantified between 0.01% and 0.06%. Also, the identified pattern of productivity effects of the 4IR technologies would conform to the productivity J-curve, lending support to the view of GPT nature for these technologies.

Edquist *et al.* (2019) study the economy-wide effect of IoT adoption, finding an elasticity of Total Factor Productivity (TFP) growth of 0.023%. Great and Michaels (2018) look at the automation effect on industry growth across OECD economies, finding that industrial robots would have spurred the growth rate of labour productivity by 0.36% annually, accounting for 15% of aggregate productivity growth since 1997.

Haskel *et al.* (2021) seek to quantify the aggregate multifactor productivity (MFP) effect of AI investment with the lens of National Accounts. As most intangible assets, AI investments are largely mis-measured and hence their productivity effect may be understated, in principle contributing to explain the widespread productivity slowdown. Looking at the dynamics of intangible investment complementary to AI, such as design, training, and business process re-engineering, these authors infer that AI investment are highly un-measured but, nonetheless do not appear to give any effect to MFP growth.

At the firm level, using ORBIS-IP data Benassi *et al.* (2021) pioneeringly show that multinational enterprises (MNE) developing 4IR such as wireless technologies and (to a smaller extent) AI have statistically significant higher levels of productivity between 2009 and 2014: the estimated elasticity of log-TFP to stock of 4IR patents is around 0.03-0.04.[2] Damioli *et al.* (2021) detect for a global sample of 5,257 firms, that patenting in the field of AI is associated with a 0.03% higher productivity level since 2009.

Behrens and Trunschke (2020) match the Mannheim Enterprise Panel (MUP) from ZEW data set to PATSTAT data set to analyse the impact on sales of knowledge accumulated in the fields of 4IR technologies by German companies. They find an output elasticity of 0.02% with respect to the 4IR patent stock after controlling for endogeneity issues (0.04% for small companies). Complementarily to the previous work on the productivity effect of AI production, Behrens *et al.* (2021) study the effect of AI adoption on TFP levels on a cross-section of German companies (4,300 units) using survey information from the Mannheim Innovation Panel (MIP) from ZEW-FDZ. Internally-developed AI systems exert a positive impact on TFP when supported by complementary intangible investment. However, firms which purchase on the market AI systems and integrate them with an internal data infrastructure, gain an additional increase in productivity (0.037%).

Evidence for the United States indicates that AI producing (patenting) companies grow faster in terms of employment (13.3%) and revenue per worker (6.8%) after the introduction of these innovations, compared to twin companies not active in the technology field of AI (Alderucci *et al.*, 2020).

Another increasingly influential stream of the literature looks at non-technological innovations; these studies point to MOCs as a key source of firms' performance and competitive advantage (Bloom & Van Reenen, 2007; 2010; Dosi & Nelson, 2010; Helfat & Martin, 2015; Teece, 2016).

[2] Igna and Venturini (2021) investigate the drivers of AI innovation across European firms, finding that AI developers are, by and large, big companies earlier engaged in ICT innovation and that AI developers extensively exploit internal learning and own technological capabilities (dynamic returns) in innovation generation.

Bloom and Van Reenen (2007, 2010) develop a theoretical framework in which the *management quality* is seen as a set of practices affecting profitability, multifactor productivity and other dimensions of firm performance that cannot be explained by *technological innovation.* Management activities are classified as *monitoring*, *target* and *incentive practices.* By conducting a survey across US and European Union covering the period 1994 and 2004, these authors build a composite indicator of management practices across firms which includes, among others, lean manufacturing and process improvements, that is, aspects to which ISO certification can be ascribed. The authors estimate an overall impact of management practices on MFP that ranges between 3.2 and 7.5% and on profits (measured by returns on capital) by 2.45% (Bloom & Van Reenen, 2007, Table I, p. 1369).

According to the evolutionary theory (Dosi *et al.,* 2000; Dosi & Nelson, 2010; Teece, 2010) firms can be seen as boundedly rational and non-optimising agents endowed with stocks of idiosyncratic and firm-specific assets that can hardly be transferred. In this context, entrepreneurial management requires complex and specific knowledge to develop a creative vision, to discover and create opportunities, to sense customer needs and anticipate marketplace responses (Teece, 2016).

Helfat and Martin (2015) review the literature on managerial capabilities and identify three core underpinnings: (i) managerial cognition, (ii) managerial human capital and (iii) managerial social capital. Most empirical studies infer managerial cognition from the association between mental models and beliefs of managers and strategic change. The latter include organisational redesign, restructuring and strategic renewal, redeployment of physical and human capital. The implementation of quality improvement methods, such as ISO 9001 standards,[3] is a challenging task involving strategic change and conditioning the whole organisational structure and routines of companies (Petrovik & Galia, 2009; Bourke & Roper, 2017). According to Diaye *et al.* (2009), the implementation of ISO 9001 certifications requires a non-trivial managerial effort, that in terms of time implementation may take between six and twelve months. Quality improvement practices can be seen as complementary to product and process innovations, as raising the opportunities to get non-technological innovations (Terziovski & Guerrero, 2014). ISO 9001 certification spurs a culture of attention for details and not only a culture of innovation (Manders, 2012).

[3] According to ISO (1998),'The ISO 9000 international standards are a set of written guidelines that make up a non-specific quality management system that can be applied to any organisation regardless of the product or service being provided.'

Currently, results concerning the impact of quality management systems, standards and certification on innovation and productivity are rather inconclusive. Standardisation supporting quality management systems should stimulate the development of a common pool of codified knowledge, orienting the innovation path undertaken by the firm, a mechanism however which is still far from being well understood (King *et al.,* 2017). Bourke and Roper (2017) explore complementarities between *soft* (*quality circles*) and *hard* quality improvement methods (*quality certification*) and their influence on *learning-by-using* and product innovation. They find positive and significant effects of quality certification, such as ISO 9001, only when *quality circles* (i.e., small groups of workers who meet regularly on a voluntary basis to discuss problems) are adopted prior to that certification. Terziovski and Guerrero (2014) look at Australian firms, finding that ISO 9001 positively affects process innovation but not product innovation.

Diaye *et al.* (2009) study the effect of ISO 9001 on productivity (value added per employee) of French manufacturing firms in the late 1990s. They use propensity score matching estimates and find that in companies completely implementing ISO 9001 the labour productivity is about 10% higher than companies non-adopting this certification.

## 3. Empirical model

Our study on productivity is based on the distance to frontier framework, largely used in earlier papers using data at different levels of aggregation (Andrews *et al.,* 2019; Cameron, 2005; Griffith *et al.,* 2004). We assume that there is a stable (long-run) relation between the productivity levels of the frontier (denoted by *f*) and laggard units (denoted by *i*). It implies that firms falling behind can exploit two forces for raising productivity, namely improvements *of* the frontier units that push forward the technological progress and technology transfers *from* the frontier. Technology transfers from the frontier can be endogenously enabled by the behaviour of the laggards; in our setting of analysis, we assume that technology transfers can be enabled by firm decisions concerning innovation investment or managerial practices.

In each of the two parts of the work, we primarily seek to identify whether companies developing novel technologies or managerial practices denote a differential in performance. Our first analysis uses data from 16 European countries to assess whether companies active in the main fields of the 4IR have a larger productivity growth. We define the frontier as the company with the highest level of productivity in a given sector $s$ at year $t$ of our global sample of firms ($c$ denotes countries). Productivity, $A$, is defined in terms of multifactor productivity (MFP), i.e. the portion of output that the firm is able to obtain from an efficient usage of inputs (see Section 4 for details):

$$Y_{icst} = A_{isct}\, F(K_{icst}, L_{icst})$$

where Y is real value added, K is real stock of fixed assets, and L is employment.

Based on the standard assumption that all companies of an industry share the same technology conditions, the level relationship between laggard and frontier's productivity can be formalised in as follows:

$$\ln A_{icst} = \alpha_0 + \alpha_1 \ln A_{fst} + \epsilon_{icst} \tag{1}$$

Next, we follow Pischke (2005) and apply a Difference-in-Difference (DiD) regression with panel data fixed effects model (FE). Here, the group-level effect is replaced by the firm-level effect, since in our case some firms are treated in some points in time and others do not. Therefore, the DiD regression is defined as:

$$\ln A_{icst} = \alpha_i + \alpha_1 D_{icst} + \boldsymbol{\alpha_2 X_{isct}} + TD_{tc} + TD_{ts} + \epsilon_{icst} \tag{2}$$

where $\alpha_i$ is the individual effect, $D$ is dummy variable with a value of 1 from the year of introduction of a 4IR-related patent in the fields 4IR and zero otherwise. $\boldsymbol{X_{isct}}$ are control variables. $TD_{ts}$ is a set of time dummies interacted with industry fixed effects used to capture technology shocks at sectoral level (such as, for instance, outward movements of the frontier). $TD_{tc}$ are country-by-year fixed effects and are used to isolate the effect of macroeconomic shocks or change in the institutional settings taking place at country level (product or labour market reforms, etc.).

$\alpha_1$ represents the differential productivity levels between firms with and without 4IR innovations; it can be therefore regarded as the Average Treatment Effect on Treated (ATET) units. ATET is identified as long as the counterfactual outcomes in absence of treatment are independent of treatment and conditional on the individual effect $\alpha_i$ and the covariates $X_{isct}$.

An equation similar to eq. (3) is estimated using the annual rate of MFP growth as dependent variable; in this context, $\alpha_1$ would identify the productivity growth premium of the firms with 4IR innovations with respect of the rest of the sample.

In the cross-country analysis, eq. (1) is estimated in dynamic terms in order to identify in what respect laggards' productivity growth is enabled by improvements *of* the technology frontier ($\beta_1$>0) and by technology transfers *from the* frontier ($\beta_2$>0), and whether the latter are fuelled by 4IR technologies. Put in other terms, with the interaction between the gap term and the dummy for the 4IR status of the firm we aim to understand if innovating companies have a differential productivity performance and are more capable to close the gap to the frontier:

$$\Delta \ln A_{icst} = \beta_{0isc} + \beta_1 \Delta \ln A_{fst} + \beta_2\, gap_{icst-1} + \beta_3\, Z_{ic}\, gap_{isct-1} + X_{isct} + TD_{tc} + \epsilon_{icst}\ .^4 \quad (3)$$

In eq. (3), $\Delta \ln A_{isct}$ is the annual rate of growth of firm *i* in sector *s* of country *c* at time *t*. $\Delta \ln A_{fst}$ is the annual productivity growth rate of the frontier firm *f* in sector *s*. $gap_{it} = \ln(A_{fst}/A_{ict})$ measures the log-distance to the sectoral frontier, which is our proxy for the productivity gap. $Z_{ics}$ is dummy indicator for those companies innovating the technological fields of the 4IR. Note that since we mostly run a panel regression model with company fixed effects, the main effect of our key variable is captured by $\beta_{0isc}$ and in the analysis we are able to identify *only* the indirect effect of $Z_{ics}$, i.e. that related to the gap. As indicated above, $\beta_2 > 0$ (<0) would denote that of laggards' productivity grows faster (slower) than in the rest of the

[4] Eq. (3) can be seen as spatial error correction mechanism (ECM) model that assumes one-to-one relation between the levels of productivity of frontier and laggard firm. -$\beta_2$ identifies the adjustment parameter (ECM term) measuring the speed of convergence towards the equilibrium.

sample. If $\beta_3 > 0$ (<0), 4IR companies have a relative advantage in productivity growth terms when they lie far from (close to) the frontier. $TD_{tc}$ identifies set of time-by-country fixed effects.[5]

In highly integrated markets, the process of productivity growth is largely influenced from companies lying at the global frontier. However, one cannot exclude that technology transfers take place even at the national level, from national leaders to firms falling behind. Accordingly, we take into account technology transfers from national and global leaders (Andrews *et al.,* 2015).

In the second part of the work, we focus on Italian companies and study the role of managerial practices on the growth trends of productivity, profitability and wages. The idea is providing evidence on whether managerial practices drive the divergence between top and the laggard companies along different dimensions of the performance. For example, we want to understand whether managerial practices help laggards reduce the distance to the firms with the highest levels of profitability or productivity, whereas they fuel between-firm wage inequality.

In our investigation on Italy, we follow Andrews *et al.* (2019) and identify differential trends in outcome variables between laggard and frontier firms, exploring the role played by innovative managerial practices (that is, ISO 9001 certification). The econometric specification used is the following:

$$\ln Y_{ist} = \alpha_0 + \alpha_1 trend + \alpha_2 F_{st} * trend + \alpha_3 Z_{is} * trend + \alpha_4 Z_{is} * F_{st} * trend + \alpha_5 X_{ist} + TD_{ts} + \epsilon_{ist} \quad (4)$$

where $i$ denote firms with i= 1, ..., N , $s$ stands for industries with s= 1, ..., 28 and $t$ years with t=2011, ...,2019. $Y$ is the outcome, namely the natural logs of MFP, labour productivity and average wages, and profit indicators. $F$ is a binary variable capturing the frontier companies in each sector, whilst *trend* is a deterministic (year) trend. $Z$ identifies a company introducing an ISO 9001 certification in the time interval between 2011 and 2019. $X_{ist}$ is a set of control variables that we describe in more detail in the next section. $TD_{ts}$ are *industry by time* dummies that we introduce to control for any shock occurring at industry level over the period under analysis.

5 In this setting, industry-by-year fixed effect, $TD_{is}$, cannot be used as they would inhibit the identification of the effect of frontier MFP growth ($\beta_1$), which is a sector-level variable changing over time.

Given the interaction terms, the coefficient $\alpha_1$ describes the growth rate of the outcome variable $Y$ for those firms below the frontier that do not introduce an ISO 9001 certification, whereas $\alpha_2$ captures the deviation from this trend for firms at the frontier. Thus, $\alpha_2 > 0$ means that companies at the frontier are growing faster than those below the frontier. $\alpha_3$ and $\alpha_4$ describe the role played by the introduction of an ISO 9001 certification for firms below and at the frontier, respectively. On the whole positive and statistically significant values for $\alpha_3$ and $\alpha_4$ indicate that quality certification raises the rate of growth of Y. More in detail, in case $\alpha_3 > 0$ with $\alpha_3 > \alpha_4$ the ISO 9001 certification helps companies below the frontier to achieve values of the outcome variable comparable to forefront firms. By contrast, when $\alpha_3 > 0$, $\alpha_4 > 0$ and $\alpha_4 > \alpha_3$ the ISO 9001 certification is contributing to the divergence in productivity, profits and wages between leaders and laggards.

According to Andrews *et al.* (2019), estimating eq. (4) by means of OLS allows to exploit between-firm variability, even though problems of unobserved heterogeneity, self-selection and reverse causality are completely neglected within this econometric specification.

Since we have a longitudinal database with time varying information concerning the first time the ISO 9001 certification has been introduced, we may set out a DID regression as done in eq. (2). In our single-country case, we give more emphasis to the introduction of post-treatment and anticipatory effects in the spirit of Autor (2003). More in detail, we follow the formalisation of Pischke (2005) and Angrist and Piscke (2009) and rewrite eq. (2) as follows:

$$\ln Y_{ist} = \alpha_i + \sum_{\tau=0}^{m} \alpha_{-\tau} D_{i,s,t-\tau} + \sum_{\tau=1}^{q} \alpha_{+\tau} D_{i,s,t+\tau} + \boldsymbol{\beta X_{ist}} + TD_{ts} + \epsilon_{ist} \tag{5}$$

where now D is our key variable ISO 9001, that takes value 1 in different points in time between 2012 and 2017[6] for treated firms and zero otherwise. The sums on the right-hand side, besides the simultaneous effect $\alpha_0 D_{i,s,t}$, allow for m lags ($\alpha_{-1;}\, \alpha_{-2;}\, \ldots$) or post-treatment effects and q leads ($\alpha_{+1;}\, \alpha_{+2;}\, \ldots$) or anticipatory effects. Significant coefficients for the lead variable tell us that causal nexus between ISO 9001 and outcome is questioned because the 'consequence' is determining the 'cause'; i.e., there is a reverse causality (Granger Test). Instead, significant coefficients for lags means that the introduction of the managerial practice may take time to show its effects on the outcomes.

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[6] We use here a time variant version of ISO 9001 variable that fits an econometric model with one lead (the anticipatory effect runs from 2012 to 2011) and two lagged effects (from 2017 to 2019). Since additional leads and lags do not add statistical significance, we opted for the most parsimonious specification to avoid drops in the observations number.

# 4. Data description and summary statistics

## 4.1. Data sources and variables

We perform the econometric analysis on the technological and managerial drivers of firm-level productivity in Europe between 2011 and 2019, just before outbreak of the pandemic. The work is divided into two parts. In the former, we seek to identify productivity differentials between companies active in the technological fields of the 4IR, with respect to the mass of European firms. This part of the work uses data from 16 countries and considers, as a whole, over 813 thousand companies and almost 5 million observations. In the latter, we focus on certifications and managerial practices and, due to data constraints, limit our analysis to the case of Italy; the second part of the work covers over 100 thousand firms and about 800 thousand observations.

The analysis is performed using three main datasets, namely BvD ORBIS Europe, OECD EPO Patreg, and ACCREDIA.[7] In the construction of MFP, we supplement such data with sector-by-country information extracted from Eurostat.

Data used in the cross-country part of the paper derives from the integration of the ORBIS Europe database (July 2021) and the OECD REGPAT database (release January 2021). We consider as 4IR-active companies those having filed at least one patent application in a set of 4IR technological fields between 2011 and 2019. We extract patent information from REGPAT database (Maraut *et al.,* 2008) which provides name disambiguation on applicants and inventors for the patents applied at the European Patent Office (source: Patstat). Patent applications matched to ORBIS comprehend three specific technological fields, namely Artificial intelligence, Robots and 3D-related inventions. These inventions represent a fraction of all inventions fuelling the Fourth Industrial Revolution. We identify Artificial intelligence and 3D-related patent applications using CPC codes provided by EPO (see Ménière *et al.,* 2017, Figure 1, pp. 87-93), whilst for Robotics-related patents we follow the IPC and CPC codes provided by WIPO (see Keisner *et al.,* 2017, Table 1, p. 40).

We use ORBIS balance sheets to derive a measure of productivity as in Gal (2013) and Andrews *et al.* (2019). We consider firms with information on value added, employment, fixed assets

[7] We wish to thank Alessandro Nisi, from Accredia statistical office, for providing micro-level database on Italian firms that introduced Iso certifications. Accredia is the sole national accreditation body appointed by the Italian government in compliance with the application of the European Regulation 765/2008. This organisation collects certifications issued in many sectors by an accredited third-party body in accordance with the standards ISO/IEC 17065, ISO/IEC 17021-1, ISO/IEC 17024.

and depreciation. Monetary variables are expressed in constant euro at 2015 prices using industry deflator from Eurostat and converted into power purchasing parities (PPP) based on OECD PPP for GDP or investment, respectively. The capital stock is derived, with the perpetual inventory method, from the constant price value of total (non-current) investment that can be extrapolated from annual data on fixed assets and capital depreciation.

Multifactor productivity is constructed in several ways, namely as superlative index or according to the Woolridge's method (2009), to ensure that our regression results are not driven by measurement issues.

In the cross-country analysis, we use superlative index measure of productivity as pioneered by Caves *et al.* (1982):

$$\ln(A_{icst}/\tilde{A}_{sc}) = \ln(Y_{icst}/\tilde{Y}_{sc}) - (1 - \tilde{s}_{isc}^{L}) \ln(K_{icst}/\tilde{K}_{sc}) - \tilde{s}_{isc}^{L} \ln(L_{icst}/\tilde{L}_{sc}) \qquad (6)$$

where $\tilde{Y}_{sc}, \tilde{K}_{sc}, \tilde{L}_{sc}$ are country-sector averages over time of our output and input measures. $\tilde{s}_{isc}^{L} = 0.5(s_{isc}^{L} + s_{sc}^{L})$ is the semi-sum of the labour share on income of the firm relatively to its sector-by-country mean, both computed over the entire time interval.

In the single-country analysis we follow Andrews *et al.* (2019) and estimate a measure of MFP based on the Wooldridge's procedure. Wooldrige (2009) addresses input endogeneity in the production function estimation by implementing a one-step GMM framework in the semi-parametric method originally developed by Olley and Pakes (1996) and Levinson and Petrin (2003). To get a measure of MFP, we estimate the following production function:

$$\ln Y_{it} = \beta_k^s \ln K_{it} + \beta_l^s \ln L_{it} + g(\ln K_{it-1}, \ln M_{it-1}) + \eta_t + u_{i,t} \qquad (7)$$

where $Y$ is the value added, $K$, $L$ and $M$ are capital stock, labour and materials, respectively. $\eta_t$ are time dummies. $g(.)$ is a 3rd degree polynomial function including all base terms, 2nd and 3rd order interactions of $\ln K_{it-1}$ and $\ln M_{it-1}$. $\ln L_{it-1}$ is used as an instrument along with all terms containing $\ln K_{it}$, $\ln K_{it-1}$ and $\ln M_{it-1}$, which act as instruments for capital and labour. Given differences across industry technologies, we estimate 28 industry-specific output elasticities ($\beta_k^s$ and $\beta_l^s$) and calculate firm-level MFPs. We alleviate the omitted price bias (Van Beveren, 2012) by applying a mark-up correction proposed by Andrews *et al.* (2019).[8]

[8] Since the mark-up $\mu_{i,t} = \frac{P}{MC}$ can be seen as the ratio between output elasticity and output share of the variable input (labour), we can empirically approximate it as $\mu_{i,t} = \frac{\widehat{\beta_l^s}}{\widehat{ws}_{i,t}}$, where the numerator is the estimated output elasticity to labour and the denominator is the adjusted wage share (see Andrews *et al.* 2019 for more details).

In the part of the study focused on Italy, we consider labour productivity (value added per employees), average labour costs (labour costs per employees) and profits as outcome variables. The average labour costs approximate the average wages paid by firms. Since we are especially interested in the trend and annual variation of average labour costs, we assume that wages mainly contribute to movements and trends of this variable.[9] As for profits, we use two alternative measures, that is, profit margin and return on assets (ROA). The former is the ratio between profit/losses before tax and operating revenues; the latter is the ratio of profit/losses before tax to total assets. Profit margin informs investors about a firm capacity in turning sales into profits. ROA is instead a measure of management effectiveness in gaining profits with the available assets and it is normally higher in firms with low capital intensity that employ important intangible assets not reported in the book (Haryanto & Chaeriah, 2018).

We measure quality improvement practices exploiting information on firm-level use of quality certification. We use the Accredia data set, that provide complete information on number and years of introduction of ISO 9001 certifications, and match to ORBIS using the company taxcode.

From ORBIS database we also collect data on characteristics of the highest-ranking authority in charge of the organisation who has executive powers (director of the firm, top manager, chairman). This allows us to approximate the human capital of managers.

In the managerial literature is quite common to use work experience explicitly as measure of human capital (Geletkanycz & Boyd, 2011; Khanna *et al.,* 2014). Since we have information about age and appointment date of the top manager in the company, we build two proxies for the manager's human capital. The age of manager, as standing alone term, would capture generic skills. Using the appointment date, we also calculate an indicator for the tenure of the manager within the firm. More precisely, we take the ratio *firm-specific tenure of the manager/age of the manager* to capture firm-specific managerial skills.

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[9] In the multi- and single-country parts of the paper, measures of inputs and outputs are built with the same procedure. Note that to mitigate the bias induced of extreme observations, for all MFP measures mentioned above a trimming procedure has been implemented as follows (see Andrews *et al.* 2019): (i) before computing MFP, we remove companies at the top and bottom 0.5th percentiles of input and output distribution (in logs); and (ii) after MFP computation, we delete those companies with productivity levels and growth at the top and bottom 1st percentile. The trimming procedure described in step (i) is also used for the additional outcomes investigated in the single-country analysis, that is, labour productivity, average labour costs, profit margin and return on assets (ROA). For each sector and year, we define as the frontier level of the outcome variables their median values for the top 5% companies. In the cross-country investigation we distinguish between a global MFP frontier, identified pooling data for all countries and national MFP frontiers, identified using country-specific samples of the data.

We include two other controls for managerial characteristics, that is, two time invariant dummy variables for the gender of the manager and its involvement in the firm as shareholder. These controls allow to take account for the heterogeneity in ruling companies associated with gender diversity (Brewis & Linstead, 1999) and with the possibility of managerial ownership to overcome standard agency problems between management and owners (Jensen & Meckling, 1976).

Following Gal (2013), to increase estimates representativeness, in either part of the empirical analysis, we use resampling weights based on the employees in *country*industry* size_class*year* cell, extracted from the Eurostat Structural Business Statistics (SBS) database:

$$E(W_{i,t}) = \frac{Emp_{c,s,z,t}^{EurostatSBS}}{Emp_{c,s,z,t}^{ORBIS}} \tag{8}$$

where the expected value E(.) for those firms *i* that belong to the same country c (1,…16) industry s (1,…28), firm-size class z (1,…5)[10] and year t (2011,…2019) is the ratio of employees from Eurostat SBS database referring to a specific cell and the sum of employees drawn from ORBIS companies that match the same cell. The weight associated to each firm is always greater than, or equal to one.[11]

## 4.2. Summary statistics for the cross-country study

Table 1 illustrates the composition of the cross-country sample of over 813,000 companies. Germany accounts for the large majority of the sample (around one fourth). Based on our selection criterion, we are able to identify 735 companies active in the fields of the 4IR, which corresponds to 0.1% of the companies covered by our analysis. These figures are consistent with earlier works conducted at firm level in this stream of the literature (Damioli *et al.,* 2021; Igna & Venturini, 2021). The large majority of the firms active in 4IR develops AI technologies, followed by those innovating in the area of the robotics. Since companies are active in more fields, the sum of the companies active in each sub-field do exceed the total number of 4IR companies.

[10] As in Gal (2013), the five classes, that we also use throughout the empirical analysis to control for the firm-size are the following: 0-9; 10-19; 20-49; 50-249; 250 and more employees.
[11] The Eurostat SBS database present some country*industry*size_class*year cells missing. To fill single year gaps we linearly interpolate the data. However, when the overall series is missing, we use persons engaged to predict employees as in Gal (2013). In the extreme case in which neither of the above procedures can be applied, we resort to the average share of size_class categories drawn from other countries or other industries.

Table 2 illustrates some descriptive statistics on productivity performance of non-4IR and 4IR companies, and in turn sheds light on the group of AI companies. All figures are weighted with the employment share of each firm type in national samples. The first row of the table reports the relative level of log-MFP of each company with respect to the average of the industry over time: positive (negative) values imply that the majority of the companies perform better (worse) than the average in the sample. The second row illustrates the average annual rate of MFP growth. Table 2 clearly illustrates that 4IR (and AI) companies have productivity level below the mean of their own sector, but have a quite fast rate of MFP growth between 2011 and 2019. The rate of productivity growth of AI companies is not as fast as those experienced by the firms innovating in field of the robotics and additive manufacturing.

### Table 1. Composition of in the cross-country sample (16 countries): number of companies

| | TOTAL | Non-4IR | 4IR* | AI | 3D | Robotics |
|---|---|---|---|---|---|---|
| AT | 26,350 | 26,317 | 33 | 15 | 3 | 18 |
| BE | 11,054 | 11,034 | 20 | 13 | 4 | 5 |
| CZ | 12,010 | 12,007 | 3 | 2 | 0 | 1 |
| DE | 198,470 | 198,223 | 247 | 102 | 44 | 129 |
| DK | 4,851 | 4,829 | 22 | 12 | 1 | 10 |
| ES | 99,030 | 99,006 | 24 | 11 | 4 | 11 |
| FI | 15,941 | 15,921 | 20 | 12 | 3 | 8 |
| FR | 67,924 | 67,812 | 112 | 57 | 11 | 59 |
| IE | 14,289 | 14,277 | 12 | 10 | 1 | 2 |
| IT | 95,155 | 95,086 | 69 | 30 | 14 | 28 |
| NL | 36,405 | 36,384 | 21 | 12 | 5 | 7 |
| NO | 7,064 | 7,053 | 11 | 5 | 0 | 7 |
| PL | 39,957 | 39,954 | 3 | 3 | 0 | 0 |
| PT | 43,339 | 43,331 | 8 | 5 | 1 | 3 |
| SE | 31,048 | 31,022 | 26 | 11 | 3 | 15 |
| UK | 110,842 | 110,738 | 104 | 69 | 10 | 36 |
| TOTAL | 813,729 | 812,994 | 735 | 369 | 104 | 339 |

*The sum of AI, 3D and robotics innovating firms exceeds to the number of 4IR companies as companies may innovate in more tech fields.

Table 2. Productivity levels and growth by type of companies, weighted averages

| | Non-4IR | 4IR | AI |
|---|---|---|---|
| MFP level | 0.5 | -2.4 | -2.5 |
| MFP growth | 0.2 | 10.9 | 4.2 |

## 4.3. Summary statistics for the single-country study: Italy

Table 3 shows the distribution of Italian companies across the 28 industries, besides the share of firms that introduced the ISO 9001 certification and the resampling weights averaged across years and firm-size classes.

### Table 3. Italian companies, ISO 9001 certifications and resampling weights across industries

| Industries | Total | ISO 9001 | ISO 9001 _share (%) | Weights |
|---|---|---|---|---|
| Mining and quarrying | 411 | 41 | 9.98 | 2.34 |
| Food products, beverages and tobacco | 4,273 | 247 | 5.78 | 6.32 |
| Textiles, wearing apparel, leather | 4,071 | 122 | 3.00 | 5.85 |
| Wood and paper products; print. & rec. media | 2,867 | 208 | 7.25 | 5.93 |
| Coke and ref. petr. products | 103 | 5 | 4.84 | 1.71 |
| Chemicals products | 1,358 | 217 | 15.98 | 1.77 |
| Pharmaceutical products | 184 | 15 | 8.15 | 1.41 |
| Rubber, plastic and non-metal min. prod | 4,255 | 497 | 11.68 | 1.88 |
| Basic metals and metal products | 9,451 | 1,301 | 13.77 | 3.25 |
| Computer, electronics, optical products | 963 | 157 | 16.30 | 2.09 |
| Electrical equipment | 1,435 | 211 | 14.70 | 2.78 |
| Machinery | 4,927 | 475 | 9.64 | 2.27 |
| Motor vehicles and other transport equipment | 882 | 88 | 9.98 | 2.50 |
| Furniture, other manuf. & repair | 3,675 | 307 | 8.35 | 6.68 |
| Electricity | 700 | 38 | 5.43 | 3.02 |
| Water supply and waste | 1,718 | 293 | 17.06 | 2.54 |
| Construction | 11,854 | 1,677 | 14.15 | 11.65 |
| Wholesale and retail trade motor vehicles | 3,839 | 160 | 4.17 | 9.44 |
| Wholesale trade | 16,481 | 678 | 4.11 | 5.46 |
| Retail trade | 8,149 | 91 | 1.12 | 16.21 |
| Transportation and storage | 5,547 | 424 | 7.64 | 5.58 |
| Postal and courier activities | 52 | 2 | 3.88 | 7.10 |
| Accommodation and food services | 6,317 | 57 | 0.90 | 19.40 |
| Publishing, television and broadcasting | 614 | 10 | 1.63 | 4.72 |
| Telecommunications | 180 | 14 | 7.78 | 6.55 |
| Computer programming and consultancy | 1,948 | 151 | 7.75 | 7.81 |
| Real estate | 5,755 | 21 | 0.36 | 17.54 |
| Professional and sc. activities | 7,911 | 659 | 8.33 | 18.52 |
| Total | 109,919 | 8,166 | 7.43 | 9.64 |

*Notes:* Companies result from a merge between ORBIS and Accredia database and they are averages calculated over the 2011-2019 period. The second column reports companies with the ISO 9001 certification independently on the time it has been introduced. Weights are averages over time (2011-2019) and classes of firm size of the resampling weights assigned to each firm and calculated for each *industry*size_class*year* cell according to the Gal's procedure (2013) described above.

Overall, our sample covers 109,919 companies. The number of companies with ISO 9001 certification is 8,166, that is, 7.43% of the whole sample. Interestingly, the distribution of ISO certifications is not excessively skewed across industries. We observe higher frequencies of these firms in manufacturing industries with different levels of technological intensity and productivity, such as computer, electronics and optical products; chemical products; basic metals; rubber and plastic products. Likewise, among service sectors and public utilities we find above-the-mean frequencies in high- and low knowledge intensive industries, for example, computer programming and consultancy; telecommunications; construction; water supply and waste. Therefore, even in summary statistics not adjusted by industries and reporting the detail ISO/Non-ISO firms, averaged values for firms' performance suffer less from industry composition effects.

These summary statistics are reported in Table 4 where companies are distinguished according to the frontier status and the implementation of ISO 9001 certification. For each outcome we define the group of leaders (top 5%) and the laggards. The frontier status for managerial characteristics (age and firm tenure of the manager, gender, shareholder status) and other firm characteristics (capital intensity, age of firm and number of employees), that we use as control variables, refers to our key indicator of performance, that is MFP. Figures for managerial and firm characteristics referring to the other five outcome-based frontier definition are pretty similar to those reported on Table 4 and are available upon request.

## Table 4. Firm performance and managerial characteristics

| | Below Frontier | | | At the Frontier | | |
|---|---|---|---|---|---|---|
| | Non-ISO 9001 | ISO 9001 | Diff | Non-ISO 9001 | ISO 9001 | Diff |
| Ln(MFP) | 10.60 | 10.93 | -0.324*** | 12.93 | 12.82 | 0.106*** |
| | *(1.05)* | *(0.84)* | | *(1.44)* | *(1.29)* | |
| Ln(MFP_MU) | 10.40 | 10.88 | - 0.482*** | 12.44 | 12.31 | 0.129*** |
| | *(1.52)* | *(1.06)* | | *(1.27)* | *(1.13)* | |
| Ln(wage) | 10.65 | 10.94 | -0.291*** | 11.35 | 11.27 | 0 .083*** |
| | *(1.01)* | *(0.85)* | | *(0.47)* | *(0.40)* | |
| Ln(Labour Prod.) | 10.73 | 11.04 | -0.310** | 12.98 | 12.83 | 0.145 *** |
| | *(0.84)* | *(0.61)* | | *(0.93)* | *(0.76)* | |
| Profit Margin (%) | 2.94 | 3.81 | -0.868*** | 33.38 | 26.08 | 7.230*** |
| | *(12.32)* | *(6.57)* | | *(17.83)* | *(9.91)* | |
| ROA (%) | 1.47 | 2.42 | -0.948*** | 19.20 | 18.96 | 0.241 *** |
| | *(4.96)* | *(4.69)* | | *(6.64)* | *(5.81)* | |
| Ln(Manager Age) | 3.94 | 3.94 | -0.02** | 3.87 | 3.88 | -0.011*** |
| | *(0.26)* | *(0.25)* | | *(0.28)* | *(0.27)* | |
| Manager Tenure/Age | 0.09 | 0.08 | 0.006*** | 0.04 | 0.04 | 0.005*** |
| | *(0.12)* | *(0.11)* | | *(0.11)* | *(0.09)* | |
| Female Managers (%) | 0.17 | 0.14 | 0.025*** | 0.16 | 0.13 | 0.033*** |
| | *(0.37)* | *(0.35)* | | *(0.37)* | *(0.33)* | |
| Man_Shareholder (%) | 0.71 | 0.69 | 0.026*** | 0.60 | 0.55 | 0.053*** |
| | *(0.45)* | *(0.46)* | | *(0.49)* | *(0.50)* | |
| Ln(Age of Firm) | 2.84 | 2.89 | -0.055*** | 2.27 | 2.36 | -0.090*** |
| | *(0.81)* | *(0.73)* | | *(1.21)* | *(1.14)* | |
| Ln(Kap/labour) | 10.51 | 10.26 | 0.246*** | 10.40 | 9.90 | 0.491*** |
| | *(1.94)* | *(1.44)* | | *(2.77)* | *(2.11)* | |
| Ln(Employees) | 2.40 | 2.90 | -0.506*** | 1.92 | 2.69 | -0.775*** |
| | *(1.13)* | *(0.97)* | | *(1.45)* | *(1.31)* | |
| Obs. | *805,080* | *89,946* | | *25,652* | *2,523* | |

*Notes:* unweighted summary statistics. The number of observations and statistics for managerial characteristics refer to MFP based frontier definition. Diff is the difference between Non-ISO 9001 and ISO 9001 means reporting the significance level for a t-test where H0: Diff=0 and HA: Diff≠0; *** p<0.01, ** p<0.05.

On the whole, a different pattern emerges between leaders and laggards adopting an ISO 9001 certification in terms of outcome variables. Companies at the frontier that introduced an ISO 9001 certification show lower performance than their peers that did not adopt such an innovative managerial practice. The opposite holds for the laggards with ISO 9001 certification that reveal a better economic performance.

Conversely, there are no systematic differences in terms of managerial and firm characteristics between frontier and laggard companies. In general terms, companies introducing an ISO 9001 scheme are slightly older and more labour intensive (lower capital/labour ratio and higher number of employees) than non-adopters. ISO 9001 companies are also less frequently ruled by a female or shareholder manager/director, even though the latter are on average older and show shorter firm-specific tenure.

# 5. Technology drivers of productivity: Evidence from 16 European Union countries

As preliminary step (Table 5) we investigate the statistical difference in productivity levels and rates of MFP growth between 4IR and non-4IR (col. (1)), and between AI and non-AI companies (col. (2)). The table reports the ATET obtained estimating eq. (2) enriched with one-year lags and leads of the treatment variable to remove simultaneous feedbacks (i.e. reverse causality). DiD estimates indicate that 4IR companies do differ from the rest of the sample only in terms of MFP growth (with an effect significant at the 10% only). Conversely, AI companies reveal a superior performance both for the level (+37%) and dynamics of productivity (+58%) with respect to non-AI companies.

Results for our cross-country DTF regressions are reported in Table 6 where the focus is on the group of 4IR innovating companies (735 units), whilst we look at the sub-group of AI companies in Table 7 (369 companies). All regressions use standard errors clustered at industry level; coefficients are weighted with the employment share of each category of companies based on national population.

Table 5. Differentials in productivity levels and growth of 4IR companies (DiD regression)

| | (1)<br>4IR | (2)<br>AI |
|---|---|---|
| MFP level | 0.004 | 0.372** |
| | (0.160) | (0.169) |
| MFP growth | 0.253* | 0.586** |
| | (0.130) | (0.286) |

*Notes:* Average Treatment Effect on Treated units. Standard errors clustered at industry (NACE 2) level. Year-by country and Year-by-industry fixed effects are included in all regressions. Coefficient estimates are weighted by the employment share of each firm category. ***,**,* significant at 1, 5 and 10%.

To begin with, in col. (1) we run a baseline OLS regression including a binary, time-invariant indicator identifying companies that have introduced 4IR technologies at least once between 2011 and 2019. This dummy variable has a positive and significant coefficient, indicating that the rate of productivity growth of 4IR companies is 12% higher than the rest of the sample.

Next, to capture hard-to-measure company characteristics (technological capabilities, business organisation, etc.) that may be correlated with the firm's probability to innovate, we run our the DTF specification with fixed effect regression. This model includes as regressor the rate of MFP growth of the frontier firms, the gap term reflecting the distance between laggards and forehead companies, and the interaction between this term and the 4IR dummy; the coefficient of the latter variable would identify whether the productivity premium of 4IR companies is related to how far or close they lie behind the frontier. In col. (2), we relate productivity performance of laggard companies to the movement of the global frontier and technology transfers enabled by these market leaders; in col. (3) we restrict our attention to the nation-specific frontiers.

As in Andrews *et al.* (2019), we find that shifts in the global frontier create important opportunities for productivity growth of the laggards (0.275) but that, nonetheless, there is divergence between technology leading and backward companies, with the latter struggling to cope the productivity levels of the former group (-0.277). Interestingly, 4IR companies depart from this pattern, revealing a significantly higher ability to reduce the distance to the frontier (0.104). The same results emerge when we focus on the leaders of the national market (col. (3)). As expected, the coefficients of the MFP growth of the frontier companies and the gap term are lower in size than found for the global leaders (see col. (2)). As the gap terms reveal, the trend to productivity divergence is common to the competition at the national and international level, albeit it appears milder within national borders (see -0.184 in col. (3) vs -0.277 in col (2)). The interaction term has a coefficient which is comparable between these two regressions suggesting that 4IR companies are capable to converge to national and global frontier in a similar extent.

## Table 6. Productivity growth and 4IR innovating companies

| | (1) | (2) Global | (3) National | (4) Global | (5) National | (6) Global | (7) National |
|---|---|---|---|---|---|---|---|
| 4IR firm | 0.121* | | | 0.048 | -0.117 | | |
| | (0.074) | | | (0.204) | (0.427) | | |
| 4IR firm x gap | | 0.104** | 0.112*** | 0.060*** | 0.092** | 0.229** | 0.136*** |
| | | (0.042) | (0.028) | (0.017) | (0.036) | (0.088) | (0.027) |
| Frontier MFP growth | | 0.275*** | 0.142*** | 0.270*** | 0.141*** | 0.346*** | 0.184*** |
| | | (0.053) | (0.020) | (0.051) | (0.020) | (0.074) | (0.019) |
| Gap | | -0.277*** | -0.184*** | -0.266*** | -0.156*** | -0.230*** | -0.101*** |
| | | (0.083) | (0.029) | (0.079) | (0.020) | (0.068) | (0.026) |
| Employment | | | | | | -0.249** | -0.259** |
| | | | | | | (0.111) | (0.119) |
| Age | | | | | | 0.257*** | 0.227** |
| | | | | | | (0.070) | (0.108) |
| 4IR dummy | Time invariant | Time invariant | Time invariant | Time variant | Time variant | Time invariant | Time invariant |
| Estimator | OLS | FE | FE | FE | FE | FE | FE |
| Obs. | 4,943,238 | 4,938,135 | 4,937,086 | 4,938,135 | 4,937,086 | 4,572,327 | 4,571,487 |
| R-squared | 0.003 | 0.059 | 0.043 | 0.060 | 0.042 | 0.057 | 0.048 |

*Notes:* The dependent variable is the annual rate of MFP growth. Standard errors clustered at industry (NACE 2) level. Year-by-country fixed effects are included in all regressions. OLS estimates are reported in in col. (1). FE estimates are reported in cols. (2)-(7). Coefficient estimates are weighted by the employment share of each firm category on national population. ***,**,* significant at 1, 5 and 10%.

In columns (4) and (5), we use a time-varying dummy to denote the 4IR status of the firm; specifically, this variable is equal to 1 only in those years in which new digital technologies are brought to the market by the applicant (and zero otherwise). This exercise is helpful as it allows to identity the main effect of the 4IR status, proving whether these companies are able to grow faster irrespectively of whether they are close or far from the technology leader. Estimates in cols. (4) and (5) suggest that 4IR companies exploit the growth potential of the new technologies to close the gap, as the main effect of the 4IR dummies is abundantly not significant.

In the last two columns of Table 6, we run our benchmark regressions, based on the time-invariant binary indicator, by including a set of control variables available from ORBIS balance sheets on a large scale. We use proxies for the company size and company age, respectively measured with the number of employees and years from the firm establishment (both taken in logs). Estimates in col. (6) and (7) do largely confirm our earlier findings; probably due to the reduction in the regression sample's size, we find a greater effect of 4IR technologies on the catch-up of laggards towards the global frontier (0.229); in absolute terms, this effect is comparable to the one exhibited by non-4IR companies.

Table 7 presents a parallel regression analysis for the group of companies developing AI innovations. As discussed extensively in Section 2, these technologies are regarded as the key enabler of the Fourth Industrial Revolution and, in this respect, a stronger boost on productivity growth could be expected for this group of innovations. However, these technologies are also argued to act as GPT, i.e., they diffuse across companies and fuel complementary innovative investment quite slowly over time, implying that these technologies may spur productivity growth in a relatively long interval with respect to that of the present analysis.

Results for AI companies in Table 7 are largely similar to those found above. Firms innovating in AI are characterised by a faster MFP growth compared to the rest of the sample and experience a more rapid catch-up process.

### Table 7. Productivity growth and AI innovating companies

| | (1) | (2) Global | (3) National | (4) Global | (5) National | (6) Global | (7) National |
|---|---|---|---|---|---|---|---|
| AI firm | 0.183* | | | 0.069 | -0.078 | | |
| | (0.094) | | | (0.267) | (0.544) | | |
| AI firm x gap | | 0.276*** | 0.140*** | 0.271*** | 0.142*** | 0.342*** | 0.181*** |
| | | (0.053) | (0.020) | (0.052) | (0.020) | (0.068) | (0.018) |
| Frontier MFP growth | | -0.279*** | -0.175*** | -0.266*** | -0.156*** | -0.225*** | -0.084*** |
| | | (0.084) | (0.023) | (0.080) | (0.020) | (0.068) | (0.019) |
| Gap | | 0.185*** | 0.133*** | 0.075* | 0.105** | 0.327*** | 0.133*** |
| | | (0.063) | (0.026) | (0.037) | (0.044) | (0.094) | (0.039) |
| Employment | | | | | | -0.266** | -0.264** |
| | | | | | | (0.104) | (0.120) |
| Age | | | | | | 0.222** | 0.200* |
| | | | | | | (0.090) | (0.109) |
| AI dummy | Time invariant | Time invariant | Time invariant | Time variant | Time variant | Time invariant | Time invariant |
| Estimator | OLS | FE | FE | FE | FE | FE | FE |
| Obs. | 4,943,238 | 4,938,135 | 4,937,086 | 4,938,135 | 4,937,086 | 4,572,327 | 4,571,487 |
| R-squared | 0.004 | 0.060 | 0.043 | 0.060 | 0.043 | 0.059 | 0.048 |

*Notes:* The dependent variable is the annual rate of MFP growth. Standard errors clustered at industry (NACE 2) level. Year-by-country fixed effects are included in all regressions. OLS estimates are reported in in cols. (1). FE estimates are reported in in cols. (2)-(7). Coefficient estimates are weighted by the employment share of each firm category on national population. ***,**,* significant at 1, 5 and 10%.

An appreciable difference from estimates in Table 6 is that the productivity growth effect of AI is economically larger than found for 4IR technologies. Moreover, AI innovating companies denote an ability to close the gap to the global frontier much faster than with respect to national leaders (0.276 in col. (2) vs 0.140 in col. (3)).

# 6. Managerial drivers of productivity, profitability and wages: Evidence from Italy

Table 8 shows the results of the model in eq. (4) estimated with pooled OLS. Here, we consider our preferred dependent variables for (i) productivity, measured by MFP (Wooldridge method); (ii) profitability, measured by ROA and (iii) average wages paid by firms. Appendix Table B.1 reports results for alternative measures of productivity and profitability: iv) MFP calculated with Wooldridge method and corrected for mark-up (MFP_MU); (v) labour productivity and (vi) profit margin. We use two versions of the dummy variable indicating the presence of ISO 9001 certification. The time-invariant dummy takes value 1 for all firms owning a certification independently of the year in which it has been adopted; in this case we also include companies introducing the quality certification before 2011. These estimates are reported in Cols. (1), (3) and (6). The time-varying ISO 9001 dummy takes value 1 only in the year in which the certification has been introduced between 2012 and 2017, and zero otherwise. In these estimates (cols. (2), (4) and (6)), we introduce controls for managerial characteristics to capture potential sources of unobserved heterogeneity associated with the CEO or director's capabilities. To be noted that all specifications include controls for firm age and size and industry-by-time dummies to account for common shocks influencing the outcomes of interest. Standard errors are clustered at the industry level.

## Table 8. ISO 9001, MFP, wages and profits in the Italian companies (Pooled OLS)

| | (1) Ln(MFP) | (2) Ln(MFP) | (3) Ln(wage) | (4) Ln(wage) | (5) ROA | (6) ROA |
|---|---|---|---|---|---|---|
| ISO 9001 | 0.041 | | 0.106*** | | 0.489*** | |
| | (0.031) | | (0.026) | | (0.096) | |
| Trend | | -0.082*** | | -0.018*** | | 0.309*** |
| | | (0.001) | | (0.001) | | (0.020) |
| Frontier X trend | | 0.456*** | | 0.162*** | | 3.070*** |
| | | (0.048) | | (0.018) | | (0.261) |
| ISO 9001_12_17 X trend | | 0.008** | | 0.018*** | | 0.062*** |
| | | (0.003) | | (0.005) | | (0.017) |
| ISO 9001_12_17 X trend X frontier | | -0.049 | | -0.019 | | 0.629 |
| | | (0.050) | | (0.015) | | (0.579) |
| Ln(Manager Age) | | 0.137*** | | 0.071** | | -0.433*** |
| | | (0.016) | | (0.030) | | (0.100) |
| Manager Tenure/Age | | -0.184*** | | -0.034 | | 0.615** |
| | | (0.054) | | (0.036) | | (0.260) |
| Female Managers (%) | | -0.061*** | | -0.036*** | | -0.101* |
| | | (0.019) | | (0.013) | | (0.050) |
| Man_Shareholder (%) | | -0.101*** | | -0.042*** | | 0.498*** |
| | | (0.012) | | (0.015) | | (0.156) |
| Ln(Age of Firm) | 0.131*** | 0.111*** | 0.112*** | 0.111*** | -0.642*** | -0.354*** |
| | (0.017) | (0.014) | (0.017) | (0.015) | (0.153) | (0.119) |
| Ln(Labour Prod.) | | | 0.386*** | 0.325*** | | |
| | | | (0.040) | (0.035) | | |
| Firm-size | Yes | Yes | Yes | Yes | Yes | Yes |
| Time*Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| ISO 9001 dummy | Time Invariant | Time Variant | Time Invariant | Time Variant | Time Invariant | Time Variant |
| Observations | 840,548 | 739,207 | 874,027 | 768,169 | 875,385 | 769,311 |
| R-squared | 0.520 | 0.586 | 0.202 | 0.239 | 0.048 | 0.335 |

*Notes:* The dependent variables are MFP, average wages and ROA in levels. *Trend* is a linear trend while *frontier* is a binary variable that takes value 1 for firms at the frontier and zero otherwise. In cols (1), (3), (5) the ISO 9001 dummy takes value 1 for all firms that introduced the certification independently on time (time invariant) while in cols. (2), (4), (6) *time variant* means that ISO 9001_12_17 takes value 1 only in the year of ISO 9001 adoption and zero otherwise. The year of ISO 9001 adoption is the sub-period 2012-2017, in order to make comparable the pooled OLS with the diff-in-diff fixed effects model performed in Table 9. In the wage equation a control for labour productivity has been included. Standard errors clustered at industry (NACE 2) level. Year-by-industry fixed effects and controls for firm-size classes are included in all regressions that also use the resampling weights discussed in Section 4. ***,**,* significant at 1, 5 and 10%.

Using the time-invariant dummy for ISO 9001, we find a positive association between the certification and higher performance in two out of three outcome variables (average wages and ROA, see Table 8). Appendix Table B.1 reveals positive associations between ISO 9001 and alternative measures of productivity (i.e., MFP corrected for mark-up) and profits (profit margin). As expected, in the growth trend specifications (cols. (2), (4), (6) of Tables 8 and B.1), a diverging pattern is observed between the top 5% firms and the rest of the companies, with the former growing much faster than the latter.

Combining results from Table 8 and Table B.1 we get a clear picture about the effects of ISO 9001 certification, which seems to largely promote the catch up of Italian companies towards national leaders. With the exception of labour productivity, the interaction between certification and the trend term has a positive and significant coefficient only for laggards ( $\alpha_3$). It signals that introducing the ISO 9001 scheme helps firms bridge the gap and, at least apparently, this managerial practice seems to exert a role in equalising economies where great divergences emerge due to *winner takes all* behaviour of few superstar firms.

Our baseline pooled OLS estimation exploits only between-units variability to identify the effect of the explanatory variables, neglecting thus some important issues such heterogeneity across firms, omitted variables, reverse causality and self-selection processes. To partially mitigate these issues, we run a Diff-in-Diff estimation with a fixed effects model as in Autor (2003). Similarly to the cross-country analysis shown above, the econometric model is augmented with one lead and two lags of the treatment variable to capture anticipatory and post-treatment effects of the variable of interest. Since we want to test the reliability of results in Table 8 and Table B.1, we also distinguish between firms lying at the frontier and firms below the frontier. Should the previous results being confirmed we would observe significant impact of ISO 9001 certification only for companies below the frontier.

### Table 9. ISO 9001, MFP, wages and profits in the Italian companies (Diff-in-Diff with fixed effects)

| Ln(MFP) | (1) Whole Sample | (2) Frontier | (3) Below Frontier |
|---|---|---|---|
| ISO 9001_12_17$_{t0}$ | 0.025* | 0.005 | 0.014 |
| | (0.012) | (0.125) | (0.019) |
| ISO 9001_12_17$_{t+1}$ | -0.015 | 0.025 | -0.028 |
| | (0.016) | (0.059) | (0.019) |
| ISO 9001_12_17$_{t-1}$ | 0.049*** | 0.146 | 0.040 |
| | (0.017) | (0.097) | (0.024) |
| ISO 9001_12_17$_{t-2}$ | 0.076*** | 0.071 | 0.051** |
| | (0.023) | (0.094) | (0.020) |
| Observations | 567,897 | 26,100 | 541,797 |
| R-squared | 0.088 | 0.909 | 0.116 |
| Firms | 101,564 | 101,059 | 9,378 |

| Ln(Wage) | (1) Whole Sample | (2) Frontier | (3) Below Frontier |
|---|---|---|---|
| ISO 9001_12_17$_{t0}$ | 0.001 | 0.048 | 0.005 |
| | (0.014) | (0.068) | (0.015) |
| ISO 9001_12_17$_{t+1}$ | 0.029** | 0.104 | 0.020* |
| | (0.012) | (0.062) | (0.010) |
| ISO 9001_12_17$_{t-1}$ | 0.011 | 0.132 | 0.010 |
| | (0.013) | (0.096) | (0.013) |
| ISO 9001_12_17$_{t-2}$ | 0.006 | 0.083* | 0.008 |
| | (0.010) | (0.044) | (0.010) |
| Observations | 478,207 | 19,795 | 458,412 |
| R-squared | 0.248 | 0.408 | 0.166 |
| Firms | 102,730 | 9,437 | 100,910 |

| ROA | (1) Whole Sample | (2) Frontier | (3) Below Frontier |
|---|---|---|---|
| ISO 9001_12_17$_{t0}$ | 0.073 | -0.674 | 0.039 |
| | (0.076) | (1.242) | (0.049) |
| ISO 9001_12_17$_{t+1}$ | -0.126 | -0.718 | 0.062 |
| | (0.132) | (2.011) | (0.100) |
| ISO 9001_12_17$_{t-1}$ | -0.241 | -1.300 | 0.008 |
| | (0.176) | (1.077) | (0.091) |
| ISO 9001_12_17$_{t-2}$ | 0.009 | -0.676 | 0.425*** |
| | (0.132) | (0.616) | (0.125) |
| Observations | 478,941 | 22,123 | 456,818 |
| R-squared | 0.017 | 0.057 | 0.026 |
| Firms | 103,049 | 11,332 | 101,255 |

*Notes*: The dependent variables are MFP, average wages and ROA in levels. The regression model is a Diff-in-Diff with fixed effects and time variant treatment where ISO 9001_12_17 takes value 1 only in the year of ISO 9001 adoption and zero otherwise. The year of ISO 9001 adoption is the sub-period 2012-2017, this allows to introduce leads (ISO 9001_12_17t +1) and lags (ISO 9001_12_17t -1; ISO 9001_12_17t -2) in order to detect anticipatory effects and post-treatment effects for the period 2011-2019. Like a Granger test, statistical significance for the ISO 9001_12_17t +1 coefficient indicates reverse causality. Standard errors clustered at industry (NACE 2) level. In the wage equation a control for labour productivity has been included. Year-by-industry fixed effects and controls for time varying manager and firm characteristics (manager's and firm's age, tenure, firm-size classes) are included in all regressions that also use the resampling weights discussed in Section 4. ***,**,* significant at 1, 5 and 10%.

Estimates in Table 9 (reporting our preferred outcomes MFP, wages and ROA) include all time-varying control variables used in the pooled OLS regressions, whilst time-invariant individual manager characteristics, such as gender and shareholder status, are absorbed by the firm-level fixed effect. In the top panel, col. (1) shows the effect on MFP associated with the ISO 9001 certification for the whole sample.

The introduction of this type of managerial practice produces a simultaneous increase in MFP levels by 2.5% and lagged positive effects that show up in two years (4.9 and 7.6%, respectively). The impact estimated here for management practices is pretty comparable to that found by Bloom and Van Reenen (2007) using a composite indicator covering a larger array of managerial characteristics (from 3.2 to 7.5% the impact on MFP). A similar pattern of effects emerges also using ROA as outcome variable but not for wages, as shown by the results reported in the bottom and mid panel of Table 9.

The results for alternative measures of productivity and profits (that is MFP_MU, labour productivity and profit margin, respectively), are reported in the Appendix (see Table B.2). Here, the influence of ISO 9001 is more questionable as the coefficients for the lead variables

(*ISO 9001_12_17*$_{t+1}$) are significant and detect the potential presence of reverse causality between outcome and treatment variables (Granger test).

## 7. Discussion and conclusions

In this work, we have analysed two different drivers of firm's performance. First, we have studied the productivity effects of the Fourth Industrial Revolution technologies (4IRs) with a specific focus on Artificial Intelligence (AI). This part of the analysis uses data from 16 countries obtained by merging the OECD REGPAT database, that conveys information on the development of 4IRs and AI technologies, to ORBIS balance sheets.

Second, we have explored the role played by managerial and organisational capabilities (MOCs), especially those capturing the implementation of quality improvement methods, such as the introduction of ISO 9001 certification. This part of the study uses detailed information on ISO 9001 certifications from the Accredia database which is available only for Italian companies; hence this analysis is carried out on single-country data.

An important common trait of the two parts, related to the general purposes of the UNTANGLED project, is to provide evidence on key factors promoting (or mitigating) the uneven distribution of firm performance in Europe, looking in particular at whether 4IRs and MOCs help the laggards reduce the gap with respect to the top performers.

In the multi-country analysis, we have applied fixed effects models and found important diverging productivity trends between market leaders and companies falling behind. However, 4IR inventions (and in particular those related to the fields of AI technologies) support the catching-up of the laggards in terms of MFP performance. It is worth noting that, here, the perspective of analysis is that on product innovation (or technology development) and not process innovation (technology adoption). Our results suggest that important technological opportunities in these new fields reside outside the top performers, and probably may be seized by laggards deciding to renovate and differentiate their patent portfolios towards the most disruptive technologies. If we look at AI inventions, one important implication is that the mass of firms operating in ICT and computer equipment sectors can easily shift their production towards new lines of business related to machine learning, big data and other automation technologies. This in turn might create opportunities for new forms of employment and growth.

In the single-country analysis we have applied a similar approach but enlarged the focus to more dimensions of firm performance, namely MFP, labour productivity, wages, and profits. First, we have run a pooled OLS model finding important divergent trends between top performers and the rest of Italian companies not only in terms of MFP, but also for profits and average wages paid. As found for 4IR technologies, companies adopting innovative managerial practices such as ISO 9001 certification are found to close more easily the gap, not only in terms of MFP, but also in terms of profits and average wages.

These results are robust when we account for endogeneity issues that we address by performing a Diff-in-Diff fixed effects regression, especially for MFP and profits. Interestingly, the positive effect of the ISO 9001 scheme on these two dimensions of performance show up slowly, i.e. with some lags with respect to the introduction of this practice. By contrast, no positive effect does emerge whether we use a mark-up corrected MFP. It would suggest that laggard firms exploit ISO 9001 certification to gain some market power that then translate into higher prices and profits. The competitive advantage in these contexts is shaped by a culture of attention for detail, customer satisfaction and quality improvement. All these aspects probably guarantee the laggards a minimum profitability and then probability to survive the specific market niches. Along this perspective, however, no robust evidence emerges on reduced gaps in terms of wages paid.

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# APPENDICES

## APPENDIX A Matching between ORBIS and OECD REGPAT: Artificial Intelligence, robotics and 3D-system patent-related technologies

Data used in the cross-country part of the paper derives from the integration between ORBIS Europe database (July 2021) and the OECD REGPAT database (release January 2021). In the analysis, we consider European companies included in that have filed for at least one patent application in a set of 4IR technological fields between 2011 and 2019.

We extract patent information from REGPAT (see Maraut *et al.,* 2008), derived from the EPO Worldwide Statistical Patent database (PATSTAT), namely PATSTAT Biblio and PATSTAT EPO Register. REGPAT covers patent applications filed to the EPO from 1978 and are linked to the NUTS regions, using the addresses of both the applicants and inventors (whose information is contained in the patent documents). REGPAT contains the identification number of each patent application that allows to use patent data in connection with other patent-related information such as the number of citations, technological fields and patent holders' characteristics.

The patent applications matched to ORBIS companies between 2011-2019 do not represent the universe of matched companies' patent applications filed to the EPO, but comprehend three specific technological fields, namely Artificial intelligence, Robots and 3D-related inventions. The identification of these inventions - representing only a share of the latest generation of new technologies known as the Fourth Industrial Revolution (or, in some areas, as the Industry 4.0) - has been made combining IPC and CPC classes, as identified by the European Patent Office and the World Intellectual Property Organization. Specifically, Artificial intelligence and 3D-related patent applications represent the list of CPC symbols as outlined in Figure 1 in Ménière *et al.* (2017, pp. 87-93), while Robots-based patents applications are identified through the list of both IPC and CPC symbols as displayed in Table 1, following the approach adopted in Keisner *et al.* (2017, p. 40).

## Table A.1 List of CPC and IPC classes used to identify robots-related patent applications (WIPO-UKIPO, 2021)

| CPC | IPC |
|---|---|
| B25J9/16 | B25J009/16 |
| B25J9/20 | B25J009/18 |
| B25J9/0003 | B25J009/20 |
| B25J11/0005 | B25J009/22 |
| B25J11/0015 | B60W030 |
| B60W30 | G05D001/02 |
| B60W2030 | G05D001/03 |
| Y10S901 | |
| G05D1/0088 | |
| G05D1/02 | |
| G05D1/03 | |
| G05D2201/0207 | |
| G05D2201/0212 | |

### *The string matching approach*

The matched databases provide information on 1355 European companies in 16 countries in Europe (see Table A.2). We have initially downloaded companies' accounts from ORBIS by focusing on data useful for the string matching process, namely companies' names and their geographic location such as the full address as a single variable, city and postal codes, NUTS codes and country, and, at a later stage, we added financial and economic information for each of the inventive companies.

The string matching exercise between ORBIS company data and patent information has been implemented at the applicant's name level following three major steps (Tarasconi, 2014; Thoma & Torrisi, 2007). In the first step, the data set including the names of ORBIS companies and the data set of REGPAT are separately harmonised through a set of string operations: i.e., the removal of nonstandard ASCII characters, double spaces, punctuation, other common misspellings, stopwords (i.e. common names such as organisation or society) and legal designations (such as CORP, INC, SPA, OYJ etc.). In the second step, we rely on two types of string matching: i) the exact match, where the applicants' names are exactly the same in both databases (excluding the legal designation), and ii) an edit distance criteria (i.e. N-gram function) where names are broken into 2-grams, and a similarity score is assigned to the matched pair by computing the number of grams that the names have in common, weighted by the inverse number of occurrences in the data (Raffo & Lhuillery, 2009). Only scores above a 0.75 threshold are taken into consideration (Lotti & Marin, 2013).

In the final step, we define a *filtering* criteria that aims to removing false positives by controlling each matched pair with their respective location information – i.e. comparing matched pairs' postal codes and cities. In case no information is available on postal codes and/or cities, we extrapolate it from companies' addresses using HERE Developer's API system, an approach adopted in Morrison *et al.* (2017). As concerns the false negatives, we aimed to maximised their matches by taking into account all types of consolidation codes available in ORBIS and also active, unknown and inactive companies (although inactive companies have no financial information available in ORBIS).

### Table A.2: Total number of applicants (REGPAT) and of companies matched to ORBIS (2011-2019)

| Country | Applicants | Matched companies | |
|---|---|---|---|
| | | Counts | Percentage |
| AT | 80 | 52 | 65.0 |
| BE | 69 | 50 | 72.5 |
| CZ | 9 | 7 | 77.8 |
| DE | 585 | 425 | 72.6 |
| DK | 57 | 34 | 59.6 |
| ES | 85 | 48 | 56.5 |
| FI | 55 | 39 | 70.9 |
| FR | 413 | 200 | 48.4 |
| GR | 0 | 0 | 00.0 |
| IE | 44 | 20 | 45.5 |
| IT | 201 | 126 | 62.7 |
| NL | 99 | 56 | 56.6 |
| NO | 32 | 21 | 65.6 |
| PL | 20 | 11 | 55.0 |
| PT | 21 | 11 | 52.4 |
| SE | 116 | 64 | 55.2 |
| UK | 330 | 191 | 57.9 |
| Total | 2,216 | 1,355 | 61.1 |

*Note*: Applicants refers to a list of entities, such as private companies, individual inventors, Research Institutes and Universities (OECD REGPAT). The matched applicants are private and public companies with a VAT/tax number in ORBIS.

## Appendix A: References

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# APPENDIX B. Effects of ISO 9001 on alternative measures of productivity and profits

### Table B.1. ISO 9001, labour productivity, MFP corrected for mark-up and profit margin (Pooled OLS)

| | (1)<br>Ln<br>(MFP_MU) | (2)<br>Ln<br>(MFP_MU) | (3)<br>Ln<br>(LabProd.) | (4)<br>Ln<br>(LabProd.) | (5)<br>Profit_marg | (6)<br>Profit_marg |
|---|---|---|---|---|---|---|
| ISO 9001 | 0.201*** | | 0.019 | | 0.579*** | |
| | (0.019) | | (0.029) | | (0.115) | |
| Trend | | -0.027*** | | 0.023*** | | 0.391*** |
| | | (0.002) | | (0.002) | | (0.049) |
| Frontier X trend | | 0.456*** | | 0.267*** | | 4.428*** |
| | | (0.066) | | (0.015) | | (0.652) |
| ISO 9001_12_17 X trend | | 0.008** | | 0.008 | | 0.163*** |
| | | (0.004) | | (0.027) | | (0.044) |
| ISO 9001_12_17 X trend X frontier | | -0.049 | | -0.003 | | 0.074 |
| | | (0.071) | | (0.004) | | (0.486) |
| Ln(Manager Age) | | 0.199*** | | 0.105*** | | -0.639** |
| | | (0.052) | | (0.014) | | (0.266) |
| Manager Tenure/ Age | | -0.232*** | | -0.096** | | 1.892** |
| | | (0.070) | | (0.043) | | (0.719) |
| Female Managers(%) | | -0.137*** | | -0.051*** | | -0.311 |
| | | (0.042) | | (0.017) | | (0.269) |
| Man_Shareholder (%) | | -0.101*** | | -0.092*** | | 0.808** |
| | | (0.025) | | (0.012) | | (0.348) |
| Ln(Age of Firm) | 0.162*** | 0.143*** | 0.079*** | 0.083*** | 0.058 | -0.043 |
| | (0.024) | (0.022) | (0.016) | (0.014) | (0.276) | (0.282) |
| Ln(Kap/labour) | | | 0.170*** | 0.132*** | | |
| | | | (0.011) | (0.011) | | |
| Firm-size | Yes | Yes | Yes | Yes | Yes | Yes |
| Time*Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 10.506*** | 9.901*** | 8.876*** | 8.924*** | 2.205** | 4.225*** |
| | (0.071) | (0.210) | (0.107) | (0.087) | (0.849) | (0.814) |
| *ISO 9001 dummy* | *Time Invariant* | *Time Variant* | *Time Invariant* | *Time Variant* | *Time Invariant* | *Time Variant* |
| Observations | 839,763 | 738,399 | 874,046 | 768,188 | 869,117 | 763,642 |
| R-squared | 0.309 | 0.371 | 0.311 | 0.443 | 0.042 | 0.196 |

*Notes:* The dependent variables are multifactor productivity corrected for mark-up (for the definition of MFP_MU see Section 4), labour productivity (value added per employee) and profit margin (the ratio of profits before tax on operating revenue). They are all expressed in levels. *Trend* is a linear trend while *frontier* is a binary variable that takes value 1 for firms at the frontier and zero otherwise. In cols (1), (3), (5) the ISO 9001 dummy takes value 1 for all firms that introduced the certification independently on time (time invariant) while in cols. (2), (4), (6) *time variant* means that ISO 9001_12_17 dummy takes value 1 only in the year of ISO 9001 adoption and zero otherwise. The year of ISO 9001 adoption is the sub-period 2012-2017, in order to make comparable the pooled OLS with the diff-in-diff fixed effects model performed in Table 9. Standard errors clustered at industry (NACE 2) level. Year-by-industry fixed effects and controls for firm-size classes are included in all regressions that also use the resampling weights discussed in Section 4. ***,**,* significant at 1, 5 and 10%.

## Table B.2. ISO 9001, labour productivity, MFP corrected for mark-up and profit margin (Diff-in-Diff with fixed effects)

| Ln(MFP_MU) | (1) Whole Sample | (2) Frontier | (3) Below Frontier |
|---|---|---|---|
| ISO 9001_12_17$_{t0}$ | 0.077*** | 0.635** | 0.035 |
| | (0.027) | (0.233) | (0.031) |
| ISO 9001_12_17$_{t+1}$ | 0.067*** | 0.372** | 0.039* |
| | (0.024) | (0.148) | (0.021) |
| ISO 9001_12_17$_{t-1}$ | 0.112*** | 0.770*** | 0.059** |
| | (0.028) | (0.244) | (0.022) |
| ISO 9001_12_17$_{t-2}$ | 0.117*** | 0.470** | 0.072*** |
| | (0.035) | (0.182) | (0.020) |
| Observations | 566,237 | 25,976 | 540,261 |
| R-squared | 0.064 | 0.848 | 0.077 |
| Firms | 101,059 | 9,423 | 100,215 |
| **Ln(LabProd.)** | **(1) Whole Sample** | **(2) Frontier** | **(3) Below Frontier** |
| ISO 9001_12_17$_{t0}$ | -0.021 | -0.116 | -0.015 |
| | (0.017) | (0.138) | (0.011) |
| ISO 9001_12_17$_{t+1}$ | -0.009 | -0.284*** | -0.015 |
| | (0.011) | (0.096) | (0.012) |
| ISO 9001_12_17$_{t-1}$ | 0.005 | -0.065 | 0.001 |
| | (0.012) | (0.132) | (0.011) |
| ISO 9001_12_17$_{t-2}$ | 0.018** | -0.051 | 0.013 |
| | (0.009) | (0.072) | (0.012) |
| Observations | 478,211 | 18,120 | 460,091 |
| R-squared | 0.212 | 0.192 | 0.159 |
| Firms | 102,733 | 8,011 | 100,798 |

| Profit Margin | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Whole Sample | Frontier | Below Frontier |
| ISO 9001_12_17$_{t0}$ | -0.179 | 0.073 | -0.718 |
| | (0.183) | (0.076) | (1.279) |
| ISO 9001_12_17$_{t+1}$ | -0.339* | -0.126 | 1.133 |
| | (0.187) | (0.132) | (1.527) |
| ISO 9001_12_17$_{t-1}$ | -0.446 | -0.241 | -0.385 |
| | (0.288) | (0.176) | (0.616) |
| ISO 9001_12_17$_{t-2}$ | -0.396** | 0.009 | -1.041 |
| | (0.193) | (0.132) | (0.808) |
| Observations | 475,318 | 20,808 | 454,510 |
| R-squared | 0.016 | 0.047 | 0.018 |
| Firms | 102,362 | 9,196 | 100,344 |

*Notes:* The dependent variables are MFP, average wages and ROA in levels. The regression model is a Diff-in-Diff with fixed effects and time variant treatment where ISO 9001_12_17 takes value 1 only in the year of ISO 9001 adoption and zero otherwise. The year of ISO 9001 adoption is the sub-period 2012-2017, this allows to introduce leads (ISO 9001_12_17$_{t+1}$) and lags (ISO 9001_12_17$_{t-1}$; ISO 9001_12_17$_{t-2}$) in order to detect anticipatory effects and post-treatment effects for the period 2011-2019. Like a Granger test, statistical significance for the ISO 9001_12_17$_{t+1}$ coefficient indicates reverse causality. Standard errors clustered at industry (NACE 2) level. Control for capital/labour ratio has been included in the labour productivity equation (second panel). Year-by-industry fixed effects and controls for time varying manager and firm characteristics (manager's and firm's age, tenure, firm-size classes) are included in all regressions that also use the resampling weights discussed in Section 4. ***,**,* significant at 1, 5 and 10%.