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The modern Solow paradox. In search for explanations

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A B S T R A C T

More than 30 years ago, Robert Solow provided the first evidence of the paradoxical low return of technological progress to productivity. Today, in an era of radical technological changes, characterized by disruptive socio-economic transformations in businesses and society, the puzzle is far from being solved. This paper offers additional reflections on this issue. Stemming from the recognition that in European regions a productivity paradox still persists, this study systematically defines and empirically tests some of the sources that could explain the weak association between the adoption of new technologies and the growth of regional labour productivity. Our findings indicate that, in general, new technologies do have a positive impact on the productivity of the sectors of adoption. The propagation of this effect to the whole regional economy, however, is mitigated by sectoral employment reallocation effects towards less productive sectors.

1. Introduction

Several scholars and commentators agree that we are currently living in an era of radical technological changes leading to disruptive socio-economic transformations in businesses and society (Frey and Osborne, 2017; Brynjolfsson and McAfee, 2014).

As was the case for previous industrial revolutions, hopes and optimism on the economic and social gains stemming from these deep changes are high (Brynjolfsson and McAfee, 2014; McAfee and Brynjolfsson, 2017; Schwab, 2017). Yet, this enthusiastic narrative falls short when coming to statistics, which clash with the high productivity expectations associated with the new technologies (Acemoglu et al., 2014; Brynjolfsson et al., 2019). Put briefly, the new technologies seem unable to escape from the curse of the productivity paradox highlighted by Solow in 1987 in the case of ICT (Information and Communication Technologies) (Solow, 1987), leading some scholars to state that we live in an age of paradox (Brynjolfsson et al., 2019).

Originating in the US, the rich debate on the productivity paradox is especially relevant in the case of the European Union (EU) and its regions. In the last fifty years, EU labour productivity growth not only decoupled from the major improvements in new technology creation and adoption but it was also particularly lethargic, with a rate of growth far below that of other advanced world economies, highlighting a "transatlantic productivity gap" (Ortega-Argilés et al., 2014). Specifically in western EU countries, labour productivity growth declined from an average yearly rate of 2.4 per cent over the period 1973–1995 to 1.5 per cent between 1995 and 2006 (van Ark et al., 2008). This decline was further amplified in the post-crisis period, with labour productivity growing at a modest 0.71 per cent average yearly rate between 2013 and 2018. From a regional perspective, the evidence is even more puzzling, with huge disparities in regional labour productivity within the EU, which have broadened in the last two decades (Gómez-Tello et al., 2020).[2]

Despite the efforts, the debate on the causes and consequences of the productivity paradox is still inconclusive (Dahl et al., 2011; Van Ark et al., 2008; Moulton, 2000; Triplett, 1999; Brynjolfsson et al., 2019). However, it is more and more urgent to explain its origins in order to highlight the critical bottlenecks impeding the widespread diffusion of the productivity gains achievable through the adoption of the new technologies as well as to devise appropriate policy interventions to

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[2] It is worth mentioning that the broad literature on the empirical evidence of the productivity paradox is not restricted to labor productivity. Many works adopted alternative approaches, in particular considering total factor productivity (TFP). Although a multi-factor approach certainly allows for a more careful measurement of firms' production inputs, the empirical measurement of TFP is still controversial. Open issues in the literature concern, among others, the techniques to be adopted, the functional form of the production function and the lack of data on the stock of capital (which is amplified at the regional level). The reader can see Fragkandreas (2021) and Ortega-Argiles and McCann (2021) for a discussion on this. Based on this reasons, in the present study we analyze the productivity paradox using labor productivity.

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unlock such bottlenecks.

This paper offers a contribution in this direction. On conceptual grounds, the paper enriches existing literature by distinguishing different traditional as well as hidden or overlooked mechanisms that are the source of the weak association if not mismatch between technology adoption and labour productivity growth and by elaborating on which types of modern technologies, chiefly intelligent automation and advanced digitalisation, are more likely to be subject to each of those mechanisms. On empirical grounds, the paper tests the operation of such mechanisms in the case of EU27+UK NUTS2 regions in the period 2013–2017, suggesting possible explanations of the productivity paradox in recent times, when the advent of the new technological era is expected to deliver its effects.

The paper is organised as follows: Section 2 discusses the traditional explanations for the productivity paradox existing in the literature and proposes new ones by emphasising whether and to what extent both traditional and new explanations may apply to each of the two main groups of modern technologies, i.e. intelligent automation and advanced digitalisation. Section 3 presents the operational strategy to capture empirically the different mechanisms that gave rise to the productivity paradox while Section 4 describes the data and the econometric approach. The results are presented in Section 5 and some final remarks and policy messages are proposed in Section 6.

2. The sources of the modern productivity paradox

2.1. Traditional explanations of the productivity paradox

The literature has long debated the origins of the productivity paradox observed for the new technologies. According to Brynjolfsson et al. (2019), there are three best candidate explanations for the mismatch between technological development and labour productivity growth: concentrated distribution of productivity gains, implementation lags, and mismeasurement.

The presence of an *uneven* and *concentrated distribution* of the labour productivity gains obtainable from technology adoption to few benefiters has recently received great attention. In fact, the distance between frontier and average firms is widening in most industries, with top firms earning extraordinary profit margins (Andrews et al., 2016; Furman and Orszag, 2015; Autor et al., 2020). In order to retain the advantages achieved, those firms may engage in anticompetitive and rent-seeking behaviours, which may even dissipate the benefits stemming from the creation and deployment of the new technologies. At worst, the ensuing distortions in markets can bring welfare losses (e.g., De Loecker and Eeckhout, 2017). The amplification of the inequalities across firms, in fact, can revert into the society with detrimental distributional consequences in terms of growing inequality, polarisation in incomes and stagnating median income and declining aggregate labour share (Autor et al., 2020). Whether market concentration and the uneven distribution of labour productivity gains imply resource dissipation in trying to capture them and to cancel the aggregate benefits stemming from innovation is still an open question awaiting conclusive evidence and proof (Brynjolfsson et al., 2019). It remains however compelling that the concentration of labour productivity gains in few highly innovative and productive firms and sectors with a limited weight on the overall economy can hardly influence the dynamics of aggregate labour productivity, leading to negligible effects on labour productivity growth.

The second explanation advocated for the occurrence of the productivity paradox is the presence of *implementation lags* in the building and full-scale application of the new technologies. Major technologies such as general purpose technologies in general, and artificial intelligence more specifically, have a greater impact on the economy and welfare but it might take considerable time, more than commonly expected, to be able to grasp their tangible effects in terms of statistics (Brynjolfsson et al., 2019). These lags have two main origins. First, it takes time for the new technologies to achieve a critical mass in order to significantly affect the aggregate output (Arthur, 1990). If the adoption rate remains low, there can be adverse threshold effects, leading to negligible effects on labour productivity growth. Moreover, if technology adoption is characterised by decreasing returns, once more labour productivity gains can remain limited if not nil. The existence of threshold effects in adoption can generate *false hopes*,[3] when the adoption levels are mistakenly considered already large enough to produce sizeable effects on productivity growth but the level achieved is still insufficient in comparison with the critical mass needed to produce real effects on productivity growth. Secondly, new technologies, especially general purpose ones, which are more abstract, original and distant from direct market applications, need complementary investments, co-inventions, adjustments as well as learning from adopting firms to overcome organisational inertia and bottlenecks. The adoption of ICTs during the 1980s and 1990s testifies this delayed pattern, as shown by Brynjolfsson and colleagues in a series of studies (Brynjolfsson and Hitt, 2003; Bresnahan et al., 2002; Brynjolfsson et al., 2002; Brynjolfsson and Hitt, 2000). David (1991) draws similar conclusions for electrification. Recent evidence on the contribution of the Internet of things to labour productivity growth seems to confirm this perspective (Edquist et al., 2021).

2.2. New explanations of the productivity paradox: hidden and overlooked elements

Lastly, *mismeasurement* of output can affect the observed level of labour productivity and, thus, its growth. This explanation has been advocated by many scholars, even if with mixed evidence (e.g., Mokyr, 2014; Alloway, 2015; Feldstein, 2015; Hatzius and Dawsey, 2015; Smith, 2015). Recent studies, in fact, contend that mismeasurement issues can be hardly considered as the primary source of the observed modern paradox (Cardarelli and Lusinyan, 2015; Byrne et al., 2016; Nakamura and Soloveichik, 2015; Syverson, 2017).

While accepting in full the relevance of the possible explanations advanced in the literature for the mismatch between technological development and labour productivity growth, in this paper, we contend that this list is not exhaustive. Specifically, we claim that this list can be enriched by taking into consideration those *hidden* or *overlooked elements* that can affect the *measurement of labour productivity growth* (and that, thus, can weaken the association between technology adoption and labour productivity growth) rather than the errors in the accounting of value added and thus in the *measurement of labour productivity level*.

Starting from the hidden elements, the Solow paradox can be the outcome of *compensation mechanisms* between the evolution of value added and employment. If both value added and employment expand (or contract) because of the diffusion of the new technologies, the net effect on labour productivity growth can be nil or negligible if not negative at worst. More specifically, the compensation mechanism is the result of two distinct channels through which the adoption of new technologies influences labour productivity growth, namely *labour displacement* and *market size effects*.[4] The former takes place when firms replace workers with new machines, which has (keeping constant value added) a positive effect on labour productivity (Acemoglu and Restrepo,

[3] Brynjolfsson et al. (2019) add as a fourth explanation the possibility of overconfidence (or *false hopes*) in the potential of the new technologies and provide numerous examples of misplaced expectations on the real effects of the new technologies, their feasibility and affordability on a large scale are numerous. However, they admit that false hopes are difficult to identify and are unlikely to represent the major source of the productivity paradox.

[4] Consistently with the literature, labour productivity is conceptualised and measured as the ratio between value added at constant prices and total employment. The labour displacement and the market size mechanisms influence labour productivity growth by respectively reducing its denominator and increasing its numerator.

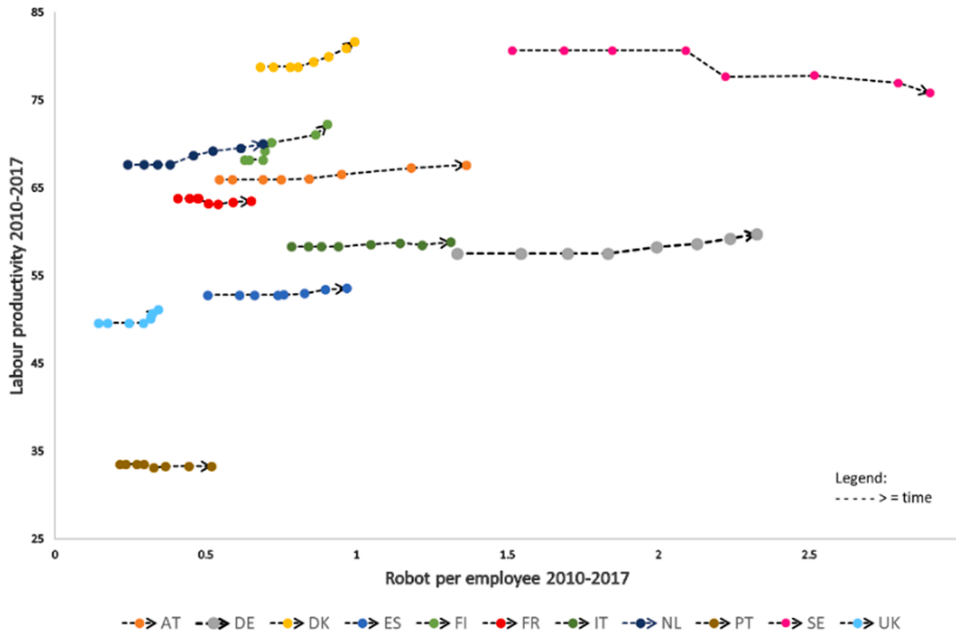

Fig. 1. Productivity and intelligent automation, 2010–2017.

2020; Autor et al., 2020). The latter is instead the result of the broadening of their market and/or of the variety of goods supplied thanks to new technology adoption. Enlarging value added and keeping constant employment has a positive effect on labour productivity. Taken together, these two effects might compensate each other, for instance when an expansion of value added occurs jointly with an increase in employment. Unfortunately, the traditional indicators of productivity growth make it impossible to disentangle these potentially opposite dynamics of value added and employment pushed by the new technologies.

Moreover, the replacement of workers with the new technologies can generate outflows of workers from more productive (i.e. innovative) adopting sectors towards less productive ones, i.e. an intersectoral *reallocation effect*, leading again to nil or negligible aggregate productivity growth. In this case, the traditional indicators masque and make it difficult to isolate the effect of such sectoral interdependencies that can have particularly harmful effects on productivity growth (MacMillan, 2014; Dauth et al., 2021).

Lastly, associated with the Solow paradox, there is the well known problem in the literature that when using labour productiivty growth at constant prices, price increases can be due to an increase in quality, or a monopolistic competitive behaviour or the synergies of the two: a monopolistic competitive behaviour can in fact stimulate quality increases, just as a novelty in the product may lead to monopolistic competitive behaviours. Independently from which of the two causes prevails, statistical institutes, which constantly adjust price indexes in order to account for the increase in quality of goods and for the appearance in the market of new goods, achieve only a rough estimate of price variation (Jany-Catrice, 2020), with the result is that growth is mis-measured. The usual statistical treatment applied to separate out inflation from increases in prices due to increases in product quality, in fact, tends to overstate inflation, assigning a too limited increase in real output reached through product quality (Aghion et al., 2019; Camagni et al., 2022). The consequence is that, when dealing with productivity increases at constant prices, the technological effects of generating product innovation and the capacity of firms to compete through an increase in quality are only partially taken into consideration.

Such an aim implies a way to measure quality of output, which remains partially overlooked by labour productivity growth analysis at constant prices. In this work we apply a method defined in Camagni et al., 2022 in line with Acemoglu et al. (2014). The rationale of the method is to consider the productivity increases at constant prices (ΔY_r) as encompassing normal, 'business as usual' quality increases in existing products, and to add sectoral differential increases in prices (in comparison with the national average inflation rate) as a measure of the quality effect embedded in new products.

What we labelled as a "quality effect" may also mirror other mechanisms leading to an increase in prices. Especially, an increase in the cost of inputs may concern either resources whose use is widespread across sectors, like oil and natural resources, or resources used only in specific economic activities, like a certain component in the automotive industry. In the former case, the effect on the differential increases in prices across sectors is expected to be limited, as the shock in the market of input spreads to the whole economy. The latter case, i.e. when the shock is instead circumscribed to a very specific sector, would raise a concern in an empirical analysis defined at a fine sectoral level. In our case, sectors are analysed at a rather aggregated level, so that a shock in the price of inputs in a specific sub-sector is assumed to have a negligible effect on the overall sectoral price index. Moreover, different increases in the cost of inputs particularly take place in the manufacturing sector which is here not disaggregated, while services, which are disaggregated, have a relatively low use of intermediate inputs.[5] Second, the change in price may derive from a shock on the demand-side of the economy. While we are not able to empirically observe these demand-side effects, we believe that this is not a limitation for the present analysis. This is because if consumers are willing to pay more for a certain good, this must reflect an increase in the perceived quality of that product.

The different explanations of the productivity paradox do not necessarily exclude one another, thus magnifying their adverse effects. Unlike previous technological revolutions, however, the present technological landscape is composed of multiple technologies. Each technology is likely to be exposed to different paradoxical mechanisms that, in isolation or combination, may hinder the unfolding of the positive effects of technology adoption on labour productivity growth. The next

[5] As a robustness check, we analysed the trend in the price of gas, electricity and crude oil and found out that all registered in the period 2013-2017 a decreasing trend. More evidence on this is available upon request.

section elaborates whether and how the new technologies are subject to the different potential sources of the productivity paradox.

2.3. Intelligent automation, advanced digitalisation and the return to the productivity paradox: stylized facts and conceptual expectations

Intelligent automation and advanced digitalisation are the two dominant modern technologies. Their adoption on a large scale is expected to radically change the organisation of manufacturing production processes as well as the creation and modes of provision of services. Both types of technologies can induce radical changes in the ways in which people work and communicate, express, inform and entertain themselves, and, importantly, do business, leading to optimism about their productivity-enhancing nature (Brynjolfsson et al., 2019).

As in the case of ICT in 1980s, however, expectations clash with statistics. Fig. 1 displays, for a selected group of Western European countries, the association between labour productivity level, measured as the ratio between value added at constant prices and total employment, and the adoption of intelligent automation, proxied by robot per employee in the period 2010–2017. In parallel, Fig. 2 presents the relationship between labour productivity and advanced digitalisation, in this case proxied by the share of firms with at least 1% of turnover from online sales, in the same period of time. While the use of robots as an indicator for automation technologies has reached a large consensus in the literature,[6] the choice about the operationalisation of the concept of digitalisation can be controversial due to the complexity and multifaceted nature of the phenomenon. The solution adopted in the paper balances several arguments.

The first option for measuring digitalisation was that of using patent data in advanced digital technologies, e.g. artificial intelligent (Edquist et al., 2021). However, we excluded this option for conceptual reasons. In fact, patents represent inventions, the most cutting-edge ones, but they do not necessarily go in tandem with adoption, especially in services which typically rank low in patenting, as remarked in the literature (Tether, 2015). However, our analysis includes both manufacturing and service sectors. For this reason, we preferred to choose an indicator of adoption of digital technologies, even if with possible limits, rather than an indicator of invention of digital technologies.

Having excluded the use of patents, data availability and cross-country comparability dictated important constraints in the choice of the final indicator of digitalisation, i.e. the share of firms with at least 1% turnover from online sales. First, this indicator is part of multi-dimensional indicators developed by both the European Union (EU) and the OECD. In fact, it is part of DESI (Digital Economy and Society Index) developed by the EU for its member states[7]; this aspect guarantees a wide coverage of countries, sectors and time spans. Moreover, this indicator is part of the multi-dimensional digital intensity index developed by the OECD at the sectoral level (Calvino et al., 2018). A particular advantage of this indicator compared with more traditional ones such as investments in ICT equipment and ICT personnel (Calvino et al., 2018), both widely used in the literature, is that it enables the emphasis to be placed on the distinctive aspect and novelty of modern digitalisation compared with the past ICT revolution, i.e. the shift towards online markets as the primary channel for market transactions and not simply the ICT endowment (Capello et al., 2022). Finally, the monitoring of the use of more advanced and recent digital technologies, e.g. cloud, machine learning and artificial intelligence, still suffer from important comparability constraints over time and across sectors, countries and regions, partly due to their newness and their limited, though increasing, diffusion.

We are also aware that considering firms with at least 1% of revenues from online sales could set a somewhat too low threshold. However, considering the time span analysed, in which online commerce was not as diffused as today especially in some European countries, this aspect should not be of particular concern.

Therefore, balancing out the availability across countries, sectors and time, made us conclude that this indicator was the most convincing solution for our analysis.

Full details on the construction of both indicators are available in the Appendix.

Starting with intelligent automation, Fig. 1 highlights that whatever the initial level of productivity and whatever the intensity of adoption, the pure correlation between productivity and adoption intensity is overall flat. In short, the increase in adoption intensity experienced in all countries in the period considered does not correlate to an increase in labour productivity.

A similar conclusion can be drawn in the case of advanced digitalisation (Fig. 2). Digitalisation deepened in the years considered but this increase in technology adoption did not match a parallel increase in labour productivity. In most countries, the correlation between technology adoption and labour productivity is again flat. There are also exceptions that, however, do not lead to better trends. In the case of the Netherlands, productivity increased even in front of a reduction of advanced digitalisation, while in Sweden productivity decreased even in front of an increase in advanced digitalisation (Maps A1 and A2 in Appendix show the diffusion of intelligent automation and advanced digitalisation).

Taken together, Figs. 1 and 2 suggest that we cannot exclude the (re-) appearance of the productivity paradox in the present technological era. The explanations of the existence of this paradox can largely differ depending on the technologies considered. Technologies can show a rather different speed of adoption, depending on the adjustment costs and on the profitability expectations from adoption. They are expected to act differently on the labour market, on market size expansion and quality increase opportunities, as well as on the distribution of gains amongst adopters.

Based on the literature and on our reasoning, we can formulate expectations regarding each possible source of the Solow paradox by type of technology (Table 1).

As regards intelligent automation, the presence of *unequal* and *concentrated distribution* to few beneficiaries of the productivity gains obtainable from technology adoption is a reasonable explanation of the paradox in the case of intelligent automation. In fact, high adoption rates in niche manufacturing segments with a relatively low weight on the overall economy are unlikely to sizeably affect the labour productivity growth of the whole economy, leading to a nil or negligible labour productivity gain (Autor et al., 2020; Acemoglu et al., 2020).

Moreover, *implementation lags* are likely to occur in the case of intelligent automation.[8] Threshold effects have been frequently documented in the adoption of different types of technologies, suggesting that low adoption rates, even if widely spread amongst different local players, lead to nil or negligible labour productivity gains (Arthur, 1990). More doubtful, instead, is whether the adoption of intelligent automation technologies is subject to decreasing returns such to nullify or at least to dampen the labour productivity gains achieved. Some authors in fact have documented the existence of increasing returns from robot adoption for specific manufacturing segments (Capello and Lenzi, 2021).

Moving to the *mismeasurement* hypothesis, it is likely that there will

[6] See Dauth et al. 2021, for Germany, Acemoglu et al., 2020, for France, Autor et al. 2020, for the US and OECD countries.

[7] https://ec.europa.eu/digital-single-market/en/integration-digital-technology, last visited 29/07/2020

[8] In the paper, whatever the technology considered, the focus is on the first form of implementation lags, i.e. threshold effects. The new 4.0 technologies are in an early stage of diffusion making it difficult to identify the complementary co-inventions and co-innovation necessary to enable their full-scale deployment.

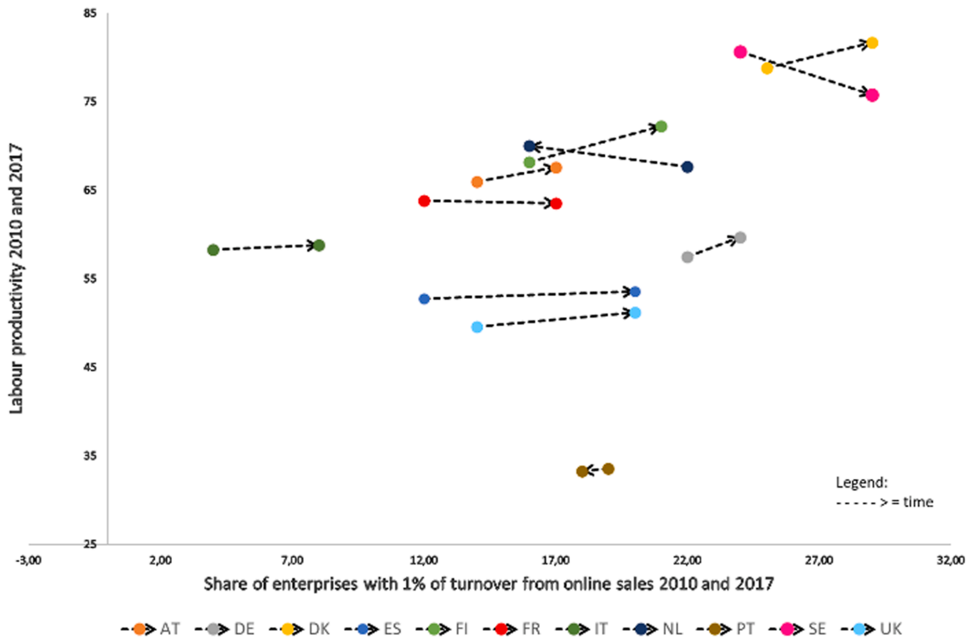

Fig. 2. *Productivity and advanced digitalisation, 2010 and 2017.*[1]

not be a *compensation mechanism* between labour displacement and market size effects. In fact, intelligent automation is expected to increase value added and, at the same time, to replace labour (Acemoglu and Restrepo, 2020), even if with some nuances. In fact, findings appear to be country-specific (Gentili et al., 2020) and occupation-specific (Georgieff and Milanez, 2021) and suggest the existence of important reallocation effects across sectors (Dauth et al., 2021). In this case, market size and labour displacement effects should rather reinforce each other, thus influencing labour productivity growth in the same (positive) direction. A different expectation concerns the *reallocation effect.* In this case, the literature suggests that workers in the manufacturing sector displaced by the new technologies are likely to be re-employed in less productive sectors (Autor and Dorn, 2013). This means that at the aggregate (i.e. regional) level, this mechanism may lead to nil or negligible labour productivity growth.

Another important element is the overlooked *quality element* when productivity growth at constant prices is measured. According to us, the adoption of intelligent automation may lead to product differentiation, allowing for price increases (e.g. customised products), probably strongly differentiated geographically. On the other hand the introduction of cost-cutting technologies allows for price decreases (Rullani and Rullani, 2018). Which one prevails is difficult to foresee, and is left to empirics.

Concerning the explanations based on the presence of *unequal* and *concentrated distribution of productivity gains* and implementation lags, the expectations are similar also in the case of advanced digitalisation. High adoption rates in niche sectors with a relatively low weight on the overall economy are unlikely to sizeably affect the productivity growth of the whole economy, leading to a nil or negligible labour productivity gain.

Similarly, *implementation lags* are likely to occur in the case of advanced digitalisation. Low adoption rates, even if widely spread amongst different local players, lead to a nil or negligible labour productivity gain (Arthur, 1990). More doubtful, instead, is whether advanced digitalisation is subject to decreasing returns such as to nullify or at least dampen the labour productivity gains achieved. In fact, digital

Table 1
Expectations on the sources of the Solow paradox by technology.

TechnologiesSources of the Solow paradox	Intelligent automation	Advanced digitalisation
Unequal and concentrated distribution	In place	In place
Implementation lags	In place	In place
Compensation mechanisms	Not in place	In place
Reallocation effects	In place	Not in place
Quality effects	Doubtful	Doubtful

This set of hypotheses is not necessarily the same when considering advanced digitalization (Table 1).

technologies adoption is typically characterised by network externalities and increasing returns (Koutsimpogiorgos et al., 2020).

As far as the *mismeasurement* hypothesis is concerned, it is possible that there will be a *compensation* between labour displacement and market size effects. In fact, in the literature advanced digitalisation is expected to increase value added but also to expand labour (i.e. gig jobs) (Autor and Dorn, 2013; Koutsimpogiorgos et al., 2020). In this case, market size and labour displacement mechanisms can offset each other, thus depressing labour productivity growth. Differently, the reallocation effect is less plausible. Productivity levels are highly heterogeneous across services, which are the sectors intensively adopting advanced digitalization, and the workers displaced by the new technologies are likely to be re-employed in both less and more productive sectors (Autor and Dorn, 2013), leading to mixed reallocation effects on aggregate productivity growth. As in the case of intelligent automation, the quality effect remains doubtful, depending on the final balance between product differentiation, allowing for price increases (customised services), and the introduction of cost-cutting technologies allowing for price decreases (Rullani and Rullani, 2018). In fact, digitalisation is by definition a technology allowing for product differentiation and for customised production, thanks to the unbundling of the product from the service and the multiplication of dematerialised products (e.g. a ride, rather than a car) sold through the network (Capello et al., 2022). This can both increase quality and lead to higher competition. Which one prevails is difficult to foresee, and is left to empirics.

In short, the best candidate explanations for the productivity paradox in the case of intelligent automation are the *reallocation effect*,

[1] In Fig. 2, we considered only data for 2010 and 2017 because for intermediate years some of the countries are missing.

the presence of *concentrated distribution* of productivity gains and the presence of *implementation lags* in the form of threshold effects. Similar considerations apply to the case of advanced digitalisation, for which the best fitting hypotheses are the presence of *concentrated distribution* of productivity gains and the presence of *implementation lags* in the form of threshold effects.

The next sections detail the empirical strategy applied to test the validity of these explanations of the productivity paradox.

3. The sources of the modern productivity paradox: measurement and methodological issues

The productivity paradox emerged as the empirical verification of a statistically insignificant association between the adoption of new technologies and regional/national labour productivity growth. More formally, we can write:

$$\Delta Y_r = \alpha(intelligent\ automation_r) + \beta(advanced\ digitalisation_r) + \gamma X_r + \varepsilon_r \tag{1}$$

where r stands for the region, Y_r represents regional labour productivity and X_r are a number of regional controls typically added in labour productivity growth models.[9] Specifically, ΔY_r is computed as the compound annual average growth of regional labour productivity in the period 2013–2017, with all independent and control variables temporally lagged and measured in 2013. A statistically insignificant value of the coefficients α and β in Eq. [2] would confirm the existence of a modern productivity paradox, consistently with what has been suggested by the literature and by the descriptive empirical evidence shown in Figs. 1 and 2. From an empirical perspective, addressing the potential sources of the paradox defined in Section 2 requires different methodological strategies, as they concern different aspects of the relationship summarised in Eq. (1).

Mismeasurement issues, as discussed above, refer to the limited informative value of ΔY_r as an indicator of labour productivity growth, since this indicator may hide and overlook at the same time several mechanisms through which new technologies may affect productivity change. Therefore, mismeasurement problems concern the left-hand side of Eq. (1), and require an alternative measurement of labour productivity growth, able to disentangle and capture what remains invisible when considering an aggregate indicator like ΔY_r.

Issues on both the unequal and concentrated distribution of productivity gains and implementation lags, on the other hand, refer to the intensity and context of adoption. They concern, for instance, the achievement of a certain threshold of users, or the occurrence of decreasing returns above a certain level of adoption. Therefore, these problems involve the right-hand side of Eq. (1), and they call for the setting of an econometric approach able to capture these non-linearities in the association between the adoption of new technologies and regional labour productivity growth.

Starting from the mismeasurement issues, our approach defines four different measures of labour productivity growth, each of them aimed at capturing elements that are typically hidden/overlooked in mainstream productivity growth analysis.

First, as explained in Section 2.1, labour productivity growth stems from two distinct effects: labour displacement and market size effects. These effects can be empirically disentangled starting from the formula of ΔY_r, adding the element $\left[\frac{VA_{r,t1}}{E_{r,t0}} - \frac{VA_{r,t1}}{E_{r,t0}}\right]$ and rearranging, as follows:

$$\begin{aligned}\Delta Y_r &= \frac{VA_{r,t1}}{E_{r,t1}} - \frac{VA_{r,t0}}{E_{r,t0}} = \frac{VA_{r,t1}}{E_{r,t1}} - \frac{VA_{r,t0}}{E_{r,t0}} + \frac{VA_{r,t1}}{E_{r,t0}} - \frac{VA_{r,t1}}{E_{r,t0}} \\ &= \underbrace{\left[\frac{VA_{r,t1}}{E_{r,t1}} - \frac{VA_{r,t1}}{E_{r,t0}}\right]}_{\Delta Y_{ld,r}=\text{Labour displacement effect}} + \underbrace{\left[\frac{VA_{r,t1}}{E_{r,t0}} - \frac{VA_{r,t0}}{E_{r,t0}}\right]}_{\Delta Y_{ms,r}=\text{market size effect}}\end{aligned} \tag{2}$$

Eq. (2) decomposes ΔY_r into two elements. The change of regional labour productivity due to a change in value added, keeping constant employment, i.e. *the market size effect*, is captured by $\Delta Y_{ms,r}$. The term $\Delta Y_{ld,r}$, on the other hand, measures the change of regional labour productivity due to a change in employment, keeping constant value added, i.e. *the labour displacement effect*. As discussed above, these two effects could either reinforce or compensate each other. If the adoption of new technologies is associated with the latter case (i.e. a compensation mechanism), this could partially explain the occurrence of a productivity paradox. In order to test this hypothesis, both $\Delta Y_{ms,r}$ and $\Delta Y_{ld,r}$ will replace ΔY_r in the empirical estimation of Eq. (1).

The second mismeasurement issue concerns the fact that labour saving technologies may induce a reallocation effect across sectors, each of them characterised by a different level of labour productivity. This mechanism may foster labour productivity growth if workers migrate from low- to high-productive sectors, but also the opposite could hold. Again, this effect is hidden within an aggregate indicator of labour productivity growth such as ΔY_r. In order to disentangle the reallocation effect from regional labour productivity growth we follow the method proposed by McMillan et al. (2014):

$$\Delta Y_r = \sum_{i=1}^{N} \theta_{r,i,t0} \Delta y_{r,i} + \underbrace{\sum_{i=1}^{N} y_{r,i,t1} \Delta \theta_{r,i}}_{\Delta Y_{re,r}=\text{Reallocation effect}} \tag{3}$$

where i denotes the sector and y_i sectoral labour productivity. Sectoral reallocation towards more (or less) productive sectors is measured by the change of the sectoral share of employment ($\Delta\theta_{r,i}$) in sectors characterised by different levels of labour productivity at the end of the period ($y_{r,i,t1}$). In this case, the reallocation effect, $\Delta Y_{re,r}$ will represent the dependent variable estimated econometrically.

The last measurement effect concerns output quality, which remains partially overlooked by labour productivity growth analysis at constant prices. In this work we apply the method proposed in Camagni et al. (2022) to isolate the quality effect on prices from other monetary effects (cost inflation, demand inflation, monetary policies, exogenous shocks), as conceptually discussed in Section 2.2. In empirical terms, we apply the difference between the sectoral deflator (δ_i, indicating the increase in sectoral prices between t_0 and t_1 at the national level) and the aggregate national deflator (δ_c for the same time period). The formula for the sectoral quality effect is therefore:

$$\Delta y_i^* = \left(\delta_{i,t1-t0} - \delta_{c,t1-t0}\right) \tag{4}$$

The difference between a sectoral price change and the national one is intended as the quality increase contribution of each sector (Δy_i^*) to aggregate regional quality increase (ΔY_r^*). In this case, the change in output quality will represent the dependent variable estimated econometrically when we aim at identifying the effects of technologies adoption on quality.

Beside mismeasurement issues, the relationship between the adoption of new technologies and labour productivity growth may find an interpretative key in the occurrence of unequal and concentrated distribution of productivity gains. In particular, if the adoption involves few firms and sectors, whose relative weight on the overall regional

[9] As discussed above (footnote 1), labour productivity is measured as the ratio between regional value added (VA_r) and total employment (E_r), so that the change of labour productivity from time t_0 to time t_1 is equal to: $\Delta Y_r = \frac{VA_{r,t1}}{E_{r,t1}} - \frac{VA_{r,t0}}{E_{r,t0}}$

Table 2
Regional labour productivity growth and the adoption of new technologies: the sources of the modern productivity paradox.

		Sources of Solow's paradox								
		Unequal and concentrated distribution		*Implementation lags*			*Mismeasurement effect*			
							market size	*labour displacement*	*reallocation*	*quality*
dependent variable	ΔY_r	ΔY_r	ΔY_r	ΔY_r	ΔY_r	ΔY_r	$\Delta Y_{ms,r}$	$\Delta Y_{ld,r}$	$\Delta Y_{re,r}$	ΔY_r^*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Robot adoption	0.095	0.105	−0.017		0.100	0.061	0.149	0.385	−0.451**	−0.062*
	(0.202)	(0.202)	(0.188)		(0.745)	(0.194)	(0.184)	(0.291)	(0.198)	(0.036)
Online sales adoption	16.322	11.048	−263.940***		18.011	−105.875*	−3.924	25.029	14.697	−0.917
	(32.586)	(31.814)	(74.690)		(32.719)	(61.837)	(30.493)	(27.315)	(14.258)	(5.666)
Specialization in robot adopting sectors	0.149*	0.217*	0.201**		0.170**	0.183**	0.186***	0.241	−0.252**	−0.026*
	(0.087)	(0.110)	(0.078)		(0.086)	(0.083)	(0.068)	(0.155)	(0.107)	(0.015)
Specialization in online sales adopting sectors	0.030	0.034	−0.168	−0.012	0.040	0.101	0.147	−0.028	−0.163**	−0.011
	(0.106)	(0.103)	(0.125)	(0.086)	(0.106)	(0.109)	(0.103)	(0.096)	(0.077)	(0.023)
Robot adoption above the median				0.556	1.513					
				(0.871)	(2.919)					
Online sales adoption above the median				−0.312		−8.533*				
				(1.397)		(4.395)				
Robot * specialization in robot adopt. sectors		−0.031								
		(0.022)								
Online sales * specialization in online adopt. sectors			5.490***							
			(1.649)							
Robot * robot adoption above the median					−0.047					
					(0.743)					
Online sales * online sales adopt. above the median						136.213**				
						(65.356)				
Share urban population	0.008	−0.050	0.621	0.177	−0.026	0.053	0.176	−0.205	−0.097	0.125
	(0.818)	(0.829)	(0.767)	(0.766)	(0.817)	(0.808)	(0.823)	(0.719)	(0.429)	(0.152)
Human capital	0.063	0.065	0.022	0.032	0.055	0.070	0.032	0.073	0.005	−0.018*
	(0.067)	(0.067)	(0.060)	(0.059)	(0.065)	(0.063)	(0.061)	(0.055)	(0.032)	(0.010)
Trade marks per capita	7.096***	6.852***	5.979***	7.053**	6.831***	6.618***	8.394***	−1.620	2.203***	0.889
	(2.627)	(2.426)	(2.218)	(2.771)	(2.597)	(2.440)	(2.957)	(1.088)	(0.617)	(0.784)
Initial productivity level	−0.212**	−0.226**	−0.252***	−0.188**	−0.218**	−0.229**	−0.194**	−0.082	−0.030	−0.029
	(0.095)	(0.096)	(0.092)	(0.089)	(0.095)	(0.098)	(0.096)	(0.054)	(0.030)	(0.025)
East EU	−5.473	−5.688	−6.774*	−3.468	−5.607	−6.155*	−2.779	−8.657***	1.989	−0.393
	(3.684)	(3.755)	(3.747)	(3.080)	(3.519)	(3.648)	(3.879)	(2.392)	(1.376)	(0.939)
Constant	5.400	7.271*	19.609***	9.939***	4.569	10.513*	2.233	−3.894	11.539***	2.750***
	(4.064)	(4.225)	(6.628)	(3.014)	(4.910)	(5.453)	(4.014)	(5.767)	(4.363)	(0.790)
Observations	260	260	260	260	260	260	260	260	260	260
R-squared	0.608	0.611	0.637	0.598	0.612	0.618	0.667	0.614	0.409	0.644

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Specifically, the specialisation sector is manufacturing in the case of the automation technology adoption and manufacturing and private services (with the exclusion of financial services) in the case of digital technologies adoption.

economy is limited, the effects on regional productivity growth might be negligible, if not nil. In order to test for this effect, the measurements of both intelligent automation and advanced digitalisation in Eq. (1) are interacted for the specialisation (in terms of share of regional employment) in the sectors typically adopting such forms of innovation, and the marginal effects of adoption at different levels of specialisation are calculated. Specifically, the specialisation sector is manufacturing in the case of the automation technology adoption and manufacturing and private services (with the exclusion of financial services) in the case of digital technologies adoption.

Finally, implementation lags are empirically addressed so to measure both threshold effects and returns to adoption. The occurrence of a threshold effect is tested for by including in Eq. (1) a dummy variable equal to one for those regions with a level of technological adoption (either intelligent automation or advanced digitalization) above the median, and equal to zero otherwise. Returns to adoption are estimated by interacting the threshold dummy variable with the level of technological adoption of the region, and the marginal effects are calculated.

Our empirical analysis covers 260 NUTS2 regions of EU27+UK,[10] and the evolution of their labour productivity between 2013 and 2017. We chose this period for two main reasons. First, intelligent automation and advanced digitalisation are both recent forms of innovation, with a relatively limited and strongly sectoral-specific diffusion in the first decade of the 2000s. Second, we want to minimise the influence of exogenous factors on regional labour productivity growth. From this perspective, the economic performance of European regions in the years prior to 2013 was still significantly affected, with different intensities, by the economic crisis (Mazzola and Pizzuto, 2020).

[10] Data are not available for Croatia, Ireland, Luxembourg and Malta. For the same reason, also the Spanish NUTS 2 regions of Ceuta and Melilla are excluded from the analysis.

Table 3
Marginal effects of the adoption of new technologies on regional labour productivity: the role of concentrated distribution and implementation lags hypotheses.

		Unequal and concentrated distribution		*Implementation lags*	
		[1]	[2]	[3]	[4]
		Robot adoption	Online sales adoption	Robot adoption	Online sales adoption
Median of specialisation	below	−0.172	−88.010***		
	above	−0.505	−22.394		
Median of adoption	below			0.100	−105.875*
	above			0.053	30.338

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

For each region in the sample, our data set collects information on both value added at current prices and employed persons in eleven economic sectors.[11] Value added at constant prices is calculated by country. Sectoral-specific deflators are provided by the EUKLEMS data repository (Stehrer et al., 2019). The same source provides also the overall country-level deflator (δ_c), used to calculate the quality effect as in Eq. (4). Notice that data on value added at the sectoral level are needed in order to estimate both the reallocation effect (Eq. (3)) and the quality effect (Eq. (4)).

The main independent variables in Eq. (1) are obviously those measuring intelligent automation and advanced digitalisation (see the Appendix for full detail). The adoption of automation technologies is captured by the robot sectoral penetration rate. National data sourced from the International Federation of Robotics in time series in the period 2008–2016 has been apportioned at the regional level by using a set of three weights accounting for the regional sectoral specialisation, the regional diffusion of broadband and the regional presence of manual occupations (i.e. blue-collar jobs). Advanced digitalisation is measured as the share of firms with 1% of turnover from online sales. National data sourced from EUROSTAT in time series in the period 2009–2016 has been apportioned at the regional level by using a set of two weights accounting for the regional sectoral specialisation and the regional diffusion of the Internet. Both robots and on-line sales are calculated as averages over the period 2011–2013 for the 260 NUTS2 regions in the sample.

Importantly, other controls (X_r in Eq. (1)) include a number of other variables capturing specific characteristics of the regional settings which may have an effect on labour productivity growth. Human capital controls for the higher skills and knowledge of the workforce (Abel et al., 2012), the share of population living in cities captures the effect of urbanisation economies on labour productivity growth, while the number of per capita registered trademarks measures other forms of innovation which may have a positive payoff on the performance of regions. The initial level of labour productivity controls for processes of convergence/divergence amongst regions. Finally, unobserved characteristics, such as the institutional setting, are accounted for by the inclusion of country dummies. Additionally, a dummy equal to one for Eastern countries and equal to zero otherwise controls for the occurrence of different paths of productivity growth between the two groups of countries. All these controls were measured in 2013, in order to avoid simultaneity with our dependent variables. Eq. (1) is estimated by the means of OLS, with robust standard errors. The next section presents our empirical findings.

4. Explanations for the modern Solow paradox

4.1. Searching for the Solow paradox in the aggregate regional productivity growth

Starting with our baseline regression, results suggest that, in general terms, whatever the technology considered, the Solow paradox is confirmed. Neither intelligent automation nor advanced digitalisation are able to affect productivity growth (Table 2, column [1]).

Starting with the hypothesis of *unequal and concentrated distribution of productivity gains*, results from Table 2 (columns [2]) and Table 3 (column [1]) suggest that this explanation of the productivity paradox does not hold for advanced digitalisation, in contrast with our expectations. The interaction term between specialisation in the robot adopting sectors and the intensity of robot adoption (Table 2, column [2]) is not significant. This is confirmed by the marginal effects in Table 3(column [1]).

When considering the possibility of *implementation lags*, Table 2 (column [4]) indicates that threshold effects seem not to be the predominant explanation of the Solow paradox. An intensity of robot adoption greater than the European median is not associated with greater productivity growth. More specifically, intelligent automation is not affected by decreasing or increasing returns to adoption (Table 2, column [5]; Table 3, columns [3]). The marginal effects of the interaction between the adoption intensity variable and the dummy flagging regions with an adoption intensity greater than the European median value are not significant (Table 3, column [3]).

As discussed above, addressing measurement issues implies the replacement of the dependent variable (ΔY_r) with alternative indicators of labour productivity growth, able to disentangle the different effects either hidden or overlooked by mainstream productivity growth analysis.

Starting from the adoption of intelligent automation technologies, our estimates only partially confirm our expectations (Table 1). Compensation mechanisms between market size (Table 1, column [7]) and labour displacement effects (Table 1, column [8]) are not in place. Nevertheless, the results shown in Table 2 are somehow surprising, as we would have expected a positive and significant effect of robot adoption on at least one of these two effects, and in particular on labour displacement. A possible explanation could be that, at the regional level, the workers displaced by the new technology are re-employed in other sectors and are not simply pushed out of the labour force. This reallocation of workers leaves the employment level in the region substantially unaltered, making the labour displacement effect negligible (Table 1, column [8]).

This interpretation is in line with the significant negative reallocation effect detected in Table 2 (column [9]), for intelligent

[11] The sectors are (the letters indicate the NACE codes): Agriculture, forestry and fishing (A), B + D-E – Industry, except construction and manufacturing (B + D + E), Manufacturing (C), Construction (F), Wholesale and retail trade, transport, accommodation and food service activities (G + H + I), Information and communication (J), Financial and insurance activities (K), Real estate activities (L), Professional, scientific and technical activities; administrative and support service activities (M-N), Public administration, defence, education, human health and social work activities (O + P + Q), Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organisations and bodies (R + S + T + U).

automation.[12] Consistent with our expectations, the adoption of intelligent automation technologies, which takes place predominantly in the manufacturing sector, pushes outflows of workers from the more productive and innovative manufacturing sector to less productive and less innovative ones, thus depressing aggregate productivity level and growth.[13]

The last explanation related to the mismeasurement hypothesis refers to the quality effect. We did not have strong ex-ante assumptions on this effect (Table 1), as companies may choose to compete either on horizontal or vertical product differentiation. Our results support the latter scenario, since the negative and significant result for the intensity of robot adoption suggests that the new technologies make adopters compete on prices rather than on quality (Table 2, column [10]).

Summing up, the most important source of the productivity paradox in the case of intelligent automation is the occurrence of a reallocation effect from highly innovative sectors towards less innovative and productive ones.

Empirical findings are not the same once we move to the interpretation of the results on advanced digitalisation.

The results on the *unequal and concentrated distribution of productivity gains* are reported in Table 2 (column [3]) and Table 3 (column [2]). The marginal effects (Table 3, column [2]) are not significant if the adopting sector is large enough (i.e. greater than the European median) but negative and significant if the adopting sector is small (i.e. smaller than the European median). In this latter case, shadow effects may dominate. In other words, in sectors of poor regional specialisation, the adoption of digital technologies seems to negatively impact regional labour productivity. This might be due to the fact that the access to a new digital market has potentially beneficial aspects (i.e. the possibility of increasing one's own market share) but also negative ones (i.e. fiercer competition). In weak sectors, the latter mechanism prevails.

As far as *implementation lags* are concerned, in Table 2 (column [4]) threshold effects do not hold in the case of advanced digitalisation. Unlike intelligent automation, however, implementation lags do exist for advanced digitalisation and operate with adverse consequences. The marginal effects of the interaction between the adoption intensity variable and the dummy flagging regions with an adoption intensity lower than the European median value is significant and negative (Table 2, column [6]). Therefore, at low levels of adoption, network externalities are so low and competition (i.e. shadow effects) so high that the effects on productivity gains are even negative (Table 3, column [4]).

In terms of mismeasurement issues, we were anticipating the occurrence of compensation mechanisms between market size and labour displacement effects. The market enlargement allowed by digitalisation was supposed to foster both the value added and the employment of adopting companies, with a compensative effect on their labour productivity. The output reported in Table 2 (columns [7] and [8]), however, contradicts this expectation. In particular, it shows a lack of a market size effect in the case of advanced digitalisation. This result can have different explanations. First, it can depend on false hopes about the achievement of a widespread adoption of technologies. Second, it can be the result of the widening of markets enabled by the new technologies that exposes both adopting and non-adopting firms to fiercer competition at the global level, with negative shadow effects.

The labour displacement, in its turn, is positive but not statistically significant (Table 2, columns [8]); it therefore does not induce any change in regional labour productivity due to the *reallocation of the workforce across sectors* (Table 2, column [9]). This confirms our expectation (Table 1), which was based on two main arguments. First, advanced digitalisation is not necessarily a labour-saving technology. Second, while intelligent automation is typically adopted by the manufacturing sector, whose level of labour productivity is generally higher than the average, advanced digitalisation is a technology transversal to very different sectors, and mainly services, whose level of labour productivity may be relatively high (as for instance in finance) or low (as in retail trade). Therefore, even if a reallocation of the workforce occurs, this might be either beneficial (if workers flow from low to high productivity sectors) or detrimental (in the opposite case) or even neutral to regional labour productivity growth.

As for intelligent automation, the expectations for the quality effect were not clear. For advanced digitalisation (Table 2, column [10]) the quality effect does seem to cancel the existence of the paradox. Probably, the cost cutting strategies and price decrease enabled by the new technologies co-exist with discrimination strategies and price increase; on balance, therefore, the net effect on productivity is negligible.

In conclusion, and quite disappointingly, most of the potential explanations for the productivity paradox do not seem adequate to highlight the mechanisms hindering the grasping of the advantages from technology adoption in terms of productivity growth. Only a few effects seem to play some role: the reallocation effect in the case of intelligent automation technologies and adverse concentrated distribution of productivity gains and implementation lags in the case of advanced digitalisation. Moreover, the policy implications of these findings are rather ambiguous. Apparently, they suggest that the competitiveness of regions does not depend on the intensity of adoption of new technologies, which might be even detrimental when the labour units displaced from innovative sectors move to less productive economic activities.

The sectoral level of analysis can represent an additional dimension useful in understanding the sources of the productivity paradox. Technology adoption in fact is not a generic process but is highly sector-specific. Sectors differ in the incentives to innovation and in the profitability gains from adoption (Malerba, 2002; Perez, 2010). Especially progressive sectors, those characterised by higher productivity levels, such as manufacturing and information services, are expected to exploit technology adoption for growth (Baumol, 1967). Therefore, sectoral heterogeneity and heterogeneity in the sectoral mix across regions can play an important role in the explanation of aggregate productivity dynamics.

In order to explore more in depth this possible explanation of the productivity paradox, the next section extends the analysis by examining the role of the different sources of the productivity paradox in illustrative groups of sectors. In particular, the sectors chosen are those characterised by the highest levels of technology adoption and for which the verification of the existence of the paradox is more compelling.[14]

4.2. Searching for the Solow paradox in the regional sectoral productivity growth

Results from regional sectoral productivity growth regressions are reported in Table 4, Panel A to D, with each panel reporting the results for a specific sector. Estimates for manufacturing and information and communication services present several similarities and, therefore, are

[12] The sectoral classification of our data obviously allow for a partial measurement of this reallocation effect. For instance, we are not able to trace the flows of workers within the manufacturing sector itself, moving from highly-innovative manufacturing sub-sectors to less-innovative (and presumably less productive) ones. Within-sectoral mechanisms of this kind are those which might explain the weak displacement effect found in our estimates (Table 1, column [8]), as discussed above.

[13] Interestingly enough, a similar depressing effect on regional aggregate productivity was signalled during the steel crisis of the 1970s in Pittsburgh, as the result of a reallocation of employers from the steel to the (low productivity) service industry (Markuses, 1988).

[14] The sectors considered are the following: manufacturing (sector C), information and communication services (sector J), wholesale and retail trade, transport, accommodation and food (sectors G, H and I), professional, scientific and technical activities; administrative and support service activities (sectors M and N).

Table 4
Sectoral heterogeneity and the modern productivity paradox.

panel a	*dependent variable*				
C - Manufacturing	ΔY_r	ΔY_r	$\Delta Y_{ms,r}$	$\Delta Y_{ld,r}$	ΔY_r^*
	[1]	[2]	[3]	[4]	[5]
Robot adoption	0.888***		0.858***	0.248*	−0.667***
	(0.228)		(0.209)	(0.129)	(0.077)
Robot adoption above the median		7.034***			
		(1.462)			
Specialization in robot adopting sectors	0.255**	0.254**	0.335***	−0.045	−0.191***
	(0.107)	(0.105)	(0.096)	(0.077)	(0.044)
Share urban population	0.930	1.540	1.375	−0.331	−1.388*
	(2.071)	(2.040)	(1.972)	(1.251)	(0.779)
Human capital	−0.335***	−0.343***	−0.311***	−0.113*	0.027
	(0.095)	(0.097)	(0.090)	(0.062)	(0.039)
Trade marks per capita	2.368	0.226	7.638	−8.379***	−1.300
	(4.639)	(4.794)	(4.628)	(2.644)	(1.169)
Initial productivity level	−0.049	−0.043	−0.071*	0.028	−0.030**
	(0.039)	(0.039)	(0.042)	(0.020)	(0.015)
East EU	2.024	2.595	6.449**	−5.561***	−7.021***
	(2.616)	(2.616)	(2.881)	(1.726)	(1.332)
Constant	11.172***	11.499***	10.678***	2.483	9.464***
	(3.467)	(3.555)	(3.404)	(1.972)	(1.378)
Observations	260	260	260	260	260
R-squared	0.253	0.274	0.472	0.417	0.414
panel b	*dependent variable*				
J - Information and communication	ΔY_r	ΔY_r	$\Delta Y_{ms,r}$	$\Delta Y_{ld,r}$	ΔY_r^*
	[1]	[2]	[3]	[4]	[5]
Online sales adoption	16.976**		7.622	13.946**	−8.228***
	(8.288)		(7.999)	(6.506)	(2.504)
Online sales adoption above the median		3.529*			
		(1.982)			
Specialization in online sales adopting sectors	0.822	0.799	−0.506	1.561**	1.270***
	(0.845)	(0.830)	(0.893)	(0.628)	(0.325)
			(7.867)		
Share urban population	2.699	2.596	4.211	−0.204	−3.780***
	(3.616)	(3.636)	(3.235)	(2.856)	(1.172)
Human capital	0.105	0.133	0.386**	−0.216*	−0.154***
	(0.148)	(0.148)	(0.149)	(0.124)	(0.053)
Trade marks per capita	−0.519	−1.189	6.760	−6.321	−3.162
	(4.976)	(4.988)	(5.054)	(4.508)	(2.962)
Initial productivity level	−0.032	−0.030	−0.028	−0.016	−0.066***
	(0.072)	(0.073)	(0.060)	(0.055)	(0.019)
East EU	2.895	3.626	16.677***	−11.443***	−5.808***
	(4.580)	(4.531)	(4.754)	(3.790)	(1.533)
Constant	−1.074	0.260	−0.342	−1.305	5.223***
	(5.688)	(5.529)	(5.268)	(4.282)	(1.994)
Observations	260	260	260	260	260
R-squared	0.042	0.038	0.314	0.330	0.196
panel c	*dependent variable*				
GHI - Wholesale and retail trade, transport, accommodation and food	ΔY_r	ΔY_r	$\Delta Y_{ms,r}$	$\Delta Y_{ld,r}$	ΔY_r^*
	[1]	[2]	[3]	[4]	[5]
Online sales adoption	18.995		6.349	18.219**	−14.680***
	(11.726)		(11.733)	(8.225)	(4.902)
Online sales adoption above the median		3.161			
		(2.000)			
Specialization in online sales adopting sectors	−1.283***	−1.320***	−1.213***	−0.603***	0.322***
	(0.260)	(0.251)	(0.243)	(0.190)	(0.113)
Share urban population	5.148	5.687*	5.851*	1.841	−2.570**
	(3.352)	(3.223)	(2.995)	(2.860)	(1.217)
Human capital	0.180	0.161	0.360***	−0.074	−0.064
	(0.135)	(0.140)	(0.126)	(0.110)	(0.049)
Trade marks per capita	−0.996	−1.138	3.197	−3.240	2.550
	(4.536)	(4.651)	(4.593)	(4.246)	(1.705)
Initial productivity level	−0.088	−0.074	−0.085	−0.040	−0.028
	(0.067)	(0.068)	(0.055)	(0.054)	(0.020)
East EU	−0.492	−0.136	11.788***	−10.601***	−3.555**
	(3.933)	(3.932)	(3.941)	(3.531)	(1.554)
Constant	34.588***	36.825***	34.564***	14.263**	−6.075
	(9.731)	(9.145)	(8.687)	(7.167)	(3.727)
Observations	260	260	260	260	260
R-squared	0.147	0.146	0.389	0.349	0.219
panel d	*dependent variable*				
MN - Professional, scientific and technical activities; administrative and support service activities	ΔY_r	ΔY_r	$\Delta Y_{ms,r}$	$\Delta Y_{ld,r}$	ΔY_r^*
	[1]	[2]	[3]	[4]	[5]
Online sales adoption	32.250		8.277	31.742*	−21.756***
	(24.298)		(23.781)	(17.504)	(7.626)
Online sales adoption above the median		1.647			

(*continued on next page*)

Table 4 (*continued*)

		(1.901)			
Specialization in online sales adopting sectors	−0.053	−0.050	−0.228	0.179	0.269**
	(0.351)	(0.360)	(0.359)	(0.253)	(0.136)
Share urban population	3.531	3.323	4.157	0.885	−3.080***
	(3.386)	(3.466)	(3.135)	(2.737)	(1.173)
Human capital	0.203	0.220	0.413***	−0.120	−0.128**
	(0.148)	(0.149)	(0.135)	(0.117)	(0.052)
Trade marks per capita	1.757	1.494	5.766	−2.509	−0.136
	(4.458)	(4.428)	(4.413)	(4.232)	(2.072)
Initial productivity level	−0.033	−0.024	−0.029	−0.016	−0.053***
	(0.074)	(0.075)	(0.059)	(0.057)	(0.019)
East EU	3.604	4.123	15.754***	−9.543**	−3.948**
	(4.257)	(4.212)	(4.398)	(3.680)	(1.667)
Constant	−0.972	−0.029	1.769	−3.305	2.278
	(5.245)	(5.074)	(4.935)	(4.017)	(1.975)
Observations	260	260	260	260	260
R-squared	0.034	0.030	0.312	0.322	0.153

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

commented jointly. Similarly, estimates for wholesale and retail trade, transport, accommodation and food and professional, scientific and technical activities, administrative and support service activities are discussed jointly, given their commonalities.

Starting with the manufacturing and information and communication sectors, estimates in Table 4 highlight that the productivity paradox vanishes in both cases, i.e. technology adoption boosts productivity growth (column [1] in both Panels A and B).[15] This favourable result is the outcome of concomitant mechanisms in place. First, there is a labour displacement effect (column [4] in both Panels A and B), a result consistent with the reallocation effect detected at the regional level (Table 2, column [4]). Second, the labour displacement effect reinforces the market size effect in the case of manufacturing, suggesting that intelligent automation does enable market expansion as expected (Panel A, column [3]).

Unexpectedly, the market size effect is not significant in the case of information and communication services. As noted in Section 4.1, a possible explanation is that the widening of markets enabled by the new technologies exposes both adopting and non-adopting firms to fiercer competition at the global level, with negative shadow effects. Importantly, these positive effects co-exist with a quality effect in favour of the paradox, similarly to what detected at the regional level. The dominant strategy behind the adoption of new technologies seems one driven by cost and price-cutting rather than one of quality improvements (column [5], Panels A and B). Finally, there seem to be no implementation lags. An intensity of adoption greater than the European median is associated with enhanced productivity growth, suggesting that the critical mass of adoption necessary to affect productivity growth has been already achieved (column [2] of both Panels A and B).

Moving to the other two groups of services, results are more nuanced. In fact, the Solow paradox seems to persist in both cases, the adoption intensity variable being not significantly associated with the productivity paradox (column [1], Panels C and D). Similar to information and communication services, the labour displacement effect seems dominant in relation to the market size effect, which is not significant (columns [3] and [4], Panels C and D). Nonetheless, the labour displacement effect is not sufficient to impact productivity growth sizeably. Consistent with the other sectors and results from Table 2 at the regional level, the quality effect speaks in favour of the paradox. Cost and price-cutting rather than quality improvement is the main reason for technology adoption (column [5], Panels C and D). Lastly, implementation lags seem at place in this case; an intensity of adoption above the European median is not associated with enhanced productivity growth, suggesting that the critical mass of adoption needed to affect productivity growth is yet to be achieved (column [2], Panels C and D).

The richness of the regional and sectoral analyses presented in this section allows drawing important and new conclusions enriching the debate on the productivity paradox, as discussed in the next section.

5. Conclusions

The inconclusiveness surrounding the debate on the productivity paradox highlighted in the introduction can find some explanations in the analyses developed in this paper. Several important messages can be drawn from our results.

The first important conclusion is that the modern Solow paradox is even more complex than in the 1980s, due to the heterogeneous nature of the technologies involved. In fact, the adoption of intelligent automation produces different effects from the adoption of advanced digital technologies. In the former case, the paradox can be explained by sectoral reallocation effects taking place at the regional level, which stem from productivity gains at the sectoral level achieved through the expansion of market size, labour saving, and large adoption. In the latter case, the paradox does not find a clear-cut explanation, either at regional or sectoral level, highlighting heterogeneous behaviours across services. In this case, implementation lags are apparently confirmed and it cannot be ruled out that a larger adoption is necessary for these technologies to display their productivity gains. This result also suggests that the disruptive transformations we are experiencing today are only a limited part of the story.

Second, the analysis conducted at the sectoral level highlights the importance of sectoral heterogeneity in the explanation of the productivity paradox. Innovative and productive sectors, such as manufacturing and information and communication services, do gain from technology adoption. In these cases, the paradox vanishes, and the adoption of the new technologies is reflected in productivity gains. For less innovative sectors, instead, the paradox persists.

Third, regardless the sector considered, however, the labour displacement effect is significant, suggesting that productivity growth comes at the cost of replacing jobs with the new technologies. This effect is particularly unexpected in the case of services as well as the lack of a market size effect, and finds possible explanations in either too low adoption and implementation lags or in the presence of an increasing global competition, difficult for European firms to face.

Fourth, the positive effects on productivity detected at the sectoral level generate negative spillover effects at the regional level in the form of reallocation effects. As far as market size and labour displacement effects do not compensate such negative effects, reallocation dominates the explanation of the productivity paradox, at least for what concerns

[15] The technology adoption variable is targeted to each specific group of sectors considered. In particular, intelligent automation, i.e. robot stock, is associated with the manufacturing sector. For the different groups of services, instead, the indicator chosen is that of online sales measured at the sectoral level (see footnote 3).

intelligent automation technologies.

Fifth, technology adoption, regardless of the sector, the technology and the level of analysis considered (i.e. sectoral or regional) is associated with cost and price cutting strategies rather than quality improvements. The quality effect is in fact persistently negative and significant, consistently with the labour displacement effect detected for all technologies and sectors.

Finally, the mismatch between the results obtained at the sectoral and regional level highlights the fact that the most innovative sectors are able to escape from the curse of the productivity paradox. However, perverse effects at the aggregate level exist, and find explanations mainly in the cost and price cutting strategy behind adoption highlighted by the negative sign of the quality effect on productivity gains and in an intersectoral reallocation effect. Non-innovative and less productive sectors become those absorbing the labour outflows generated from the adoption of the new technologies in the most innovative ones, further depressing aggregate productivity level and growth.

Important policy reflections derive from these results. First, efforts to promote productivity by investing in technology diffusion are not misplaced for the most productive sectors and can be rewarding in less innovative sectors, provided a sufficient time and adoption level are allowed. Second, efforts to raise the productivity of non-adopting sectors and their connectivity with the base ones represent compelling policy targets given the strong inter-sectoral reallocation effects in place from innovative to less innovative sectors. Up to now, in fact, more productive and innovative sectors seem unable to pull the overall productivity at the regional level, either because they have a limited weight in the regional economy or because their productivity gains are offset by the sluggish if not declining productivity in the remaining sectors of the regional economy. Finally, efforts to achieve larger market size should be put in place, replacing the survival strategies that nowadays lead the adopters to remain active on markets rather than to enlarge market shares.

CRediT authorship contribution statement

Roberta Capello: Conceptualization, Funding acquisition, Methodology, Project administration, Writing – original draft. **Camilla Lenzi:** Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Formal analysis, Writing – original draft. **Giovanni Perucca:** Conceptualization, Data curation, Investigation, Methodology, Formal analysis, Software, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix. Measuring the adoption of intelligent automation and advanced digital technologies

The indicator chosen to measure the adoption of intelligent automation technologies is the robot stock, consistent with the literature.

Data on robot adoption has been obtained from the International Robot Federation (IFR). The IFR classifies robot sales by groups of industrial sectors and country of the purchasing firm. Data are at the national level for all EU countries with the exclusion of Luxembourg and Cyprus, starting from 2004. For previous years, the sectoral breakdown is unavailable for most of the countries. The yearly robot stock has been computed by applying the perpetual inventory method with a 12% depreciation rate as recommended by the IFR, as follows:

$$\mathrm{Robot}_{n,t} = (1 - \mathrm{d})\mathrm{Robot}_{n,t-1} + \mathrm{Robot}_{n,2004}$$

Specifically, $\mathrm{Robot}_{n,t}$, the capital stock of country n at time t, is obtained as the sum of the robots purchased in the previous periods with a constant (across countries and over time) 12% depreciation rate (d). The robot stock value for the initial year was that of 2004.

National data have been apportioned at the regional (NUTS2) and sectoral level (i.e. manufacturing) by applying the simple average of a set of three weights accounting for the following aspects:

- the relevance of the manufacturing sector in the region in comparison with the country. The use of this weight is common in the scientific literature (e.g. Acemoglu and Restrepo, 2020a) and follows the expectation that regional sectoral robot adoption depends on regional sectoral specialisation, i.e. regions that are more specialised in the manufacturing sector contribute more to national robot adoption in the same sector;
- the level of broadband penetration in the region compared with the country. The use of this weight follows the expectation that robot adoption is more likely in more digitalised regions equipped with a relatively more advanced digital infrastructure, i.e. in regions more prone to adopt new technologies;
- the relevance of manual occupations in the region compared with the country. The use of this weight follows the assumption that robot adoption is meant especially to replace manual routine occupations, i.e. regions with a larger proportion of such occupations are more likely to adopt new robots.

This approach improves upon existing methods applied in the literature, in which regional apportionment is based on the sectoral dimension only (Acemoglu and Restrepo, 2020a). By using only a sectoral weight, in fact, robot adoption turns out to be affected simply by the regional sectoral mix.

The inclusion of two additional elements, instead, enables us to take into consideration the fact that regions with the same sectoral mix can show different adoption rates depending on the jobs (i.e. occupations) affected by the adoption process and the general level of technological readiness and infrastructure of the region (i.e. broadband penetration).

The source of data is EUROSTAT and, in particular, Sectoral Business Statistics (SBS) for sectoral employment data, the Labour Force Survey (LFS) for data occupational employment data.

In particular, the three weights have been computed by applying the following formulas:

- $w_1 = (Emp_{r,s} / Emp_{n,s})$

where Emp stands for the number of employees, *r* the region, *n* the country, *s* the sector;

- $w_2 = (Pop_{r,bb} / Pop_{n,bb})$

where $Pop_{r,bb}$ stands for the number of inhabitants in region *r* having access to broadband and $Pop_{n,bb}$ stands for the number of inhabitant in country *n* having access to broadband. EUROSTAT makes available only the share of persons with broadband access. In order to compute w_2, the number of inhabitants in the region (respectively, the country) with broadband access was obtained by multiplying the shares provided by EUROSTAT times the regional (respectively, national) population;

- $w_r = (Emp_{r,o} / Emp_{n,o})$

where $Emp_{r,o}$ stands for the number of employees in region *r* in manual occupations (ISCO group 8 - Plant and machine operators, and assemblers) and $Emp_{n,o}$ stands for the number of employees in country *n* in manual occupations (ISCO code 8).

As robot sales are count data and prone to ups and downs, in the econometric analysis data on regional robot adoption is averaged over the 2011–2013 period.

Data on the share of firms with at least 1% of their turnover obtained through online sales – the proxy for the adoption of digital service technologies – has been instead obtained from EUROSTAT and is available at the national level with a sufficient sectoral breakdown starting from 2009. EUROSTAT makes available only the share of firms selling online, not the actual number of firms. In order to compute the number of firms with online sales at the national level to be apportioned at the regional level, data on sectoral local units have been used, sourced from SBS.

National data have been apportioned at the regional (NUTS 2) and sectoral (i.e. C, GHI, J, MN) level by applying the simple average of two weights accounting for the following aspects:

- the relevance of the sector in the region with respect to the country. The use of this weight follows the expectation that regional sectoral online sales depend on regional sectoral specialisation, i.e. regions that are more specialised in a specific sector contribute more to national sales online in the same sector and have, thus, a greater share of firms selling on line;
- the level of internet access in the region compared with the country. The use of this weight follows the expectation that online sales are more diffused in regions with a more digitalised population, i.e. in regions more prone to adopt new technologies. Using the population with internet access as the second weight in the digitalisation indicator depends on the fact that in this case we are interested in the intensity of use of digital technologies regardless of the presence of a relatively advanced digital infrastructure, as it is instead the case of the broadband indicator.

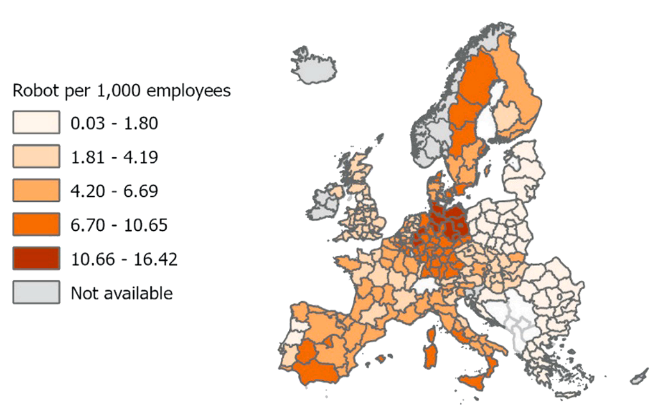
In particular, the two weights have been computed by applying the following formulas:

- $w_1 = (Emp_{r,s} / Emp_{n,s})$

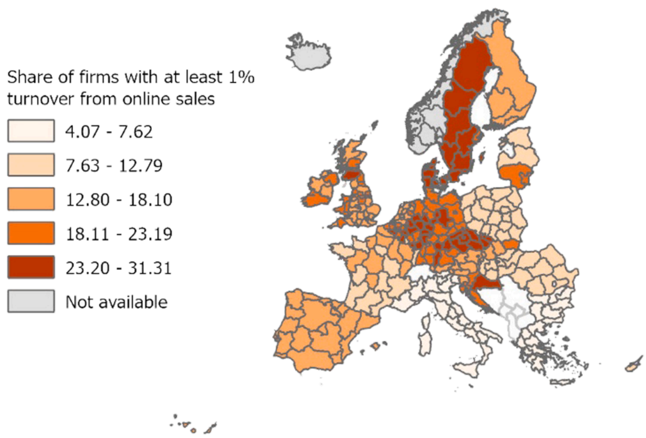
where *Emp* stands for the number of employees, *r* the region, *n* the country, *s* the sector (i.e. private services, service technology sector, service carrier sector or service induced sector, respectively). As noted above, sectoral employment data has been sourced from SBS;

- $w_2 = (Pop_{r,int} / Pop_{n,int})$

where $Pop_{r,int}$ stands for the number of inhabitants in region *r* having access to internet and $Pop_{n,int}$ stands for the number of inhabitant in country *n* having access to internet. EUROSTAT makes available only the share of persons with internet access. In order to compute w_2, the number of



Map A1. The adoption of intelligent automation technologies in European regions, 2011–2013 average.



Map A2. The adoption of advanced digital technologies in European regions, 2011–2013 average.

inhabitants in the region (respectively, the country) with internet access was obtained by multiplying the shares provided by EUROSTAT times the regional (respectively, national) population.

By this apportionment methodology, it was possible to compute the number of firms with online sales at the regional level. The regional/sectoral share of firms selling online was obtained by dividing, for each sector, the number of firms with online sales at the regional level by the number of local units obtained from SBS.

Because of data gaps in SBS at the regional/sectoral level, in the econometric analysis data on regional sectoral online sales is averaged over the period 2011–2013.

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