Spatial Economic Analysis

ISSN: 1742-1772 (Print) 1742-1780 (Online) Journal homepage: www.tandfonline.com/journals/rsea20

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To cite this article: Roberta Capello, Camilla Lenzi & Elisa Panzera (12 Aug 2025): Cities as catalysts of wage inequalities from digitalisation, Spatial Economic Analysis, DOI: 10.1080/17421772.2025.2533478

To link to this article: https://doi.org/10.1080/17421772.2025.2533478

SPATIAL ECONOMIC ANALYSIS
https://doi.org/10.1080/17421772.2025.2533478

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ABSTRACT
This paper studies the redistributive consequences of digitalisation, highlighting urbanisation economies as catalysts of wage inequalities. Digitalisation generates productivity and reinstatement effects, whose balance can vary across occupations and settlement type, increasing wage inequalities among occupational groups within regions. Occupation-specific ordinary least squares (OLS) regressions using cross-sectional data on Italian cities (NUTS3 regions) in the period 2012–2019 show low-skilled workers facing displacement and negative productivity effects, particularly in non-urban contexts. High-skilled workers in urban environments enjoy increased labour demand and wages. Consequently, urban areas experience sharper wage inequalities as digital technologies spread, concentrating wealth and amplifying disparities among occupational groups.

KEYWORDS
Digitalisation, inequalities, cities, Italian provinces

JEL J30, O31, O33, R11
HISTORY Received 4 September 2024; in revised form 4 April 2025

1. INTRODUCTION

The unbalanced effects of technological change on employment and wages are a crucial topic in the innovation studies and labour economics literature (Acemoglu, 2002; Acemoglu & Restrepo, 2019; Autor et al., 2003; Vivarelli, 1995). The technological advances enabled by the third industrial revolution at the end of the last century, in fact, are widely considered as one of the main sources of increase in wage inequalities among workers' groups (Autor & Dorn, 2013; Johnson, 1997).

With the advent of the new technological (digital) era, a complex mix of new technologies is available, whose adoption is expected to be disruptive in the way people work, entertain themselves and do business. Several studies highlight the expansionary nature of different groups of technologies (e.g., robots, artificial intelligence (AI), etc.), in terms of gross domestic product (GDP) and, to some extent, productivity (Capello et al., 2022a; Capello & Lenzi, 2023; Ciffolilli & Muscio, 2018; Paiva Santos et al., 2018).

Concerning the employment and wage redistribution effects of the diffusion of the new digital technologies, however, most evidence is about automation technologies measured in terms of robot adoption.[1] Beside quantifying the displacement effect of robot adoption, these studies

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/17421772.2025.2533478

highlight the compression of low-skilled workers wage bill share, still with important nuances depending on the country, period or sector examined. In fact, the aggregate effect on worker groups wage bill share is the balance between a positive productivity effect for those occupations intensive of not (yet) automatable tasks and a displacement effect for occupations intensive of automated tasks, with the former partially mitigating the latter (Acemoglu & Restrepo, 2019; Dinlersoz & Wolf, 2018; Dixon et al., 2021).[2] Furthermore, automation has also been identified as one of the sources of the decline of labour share of income, as it increases capital income. By driving wage stagnation for low-income workers while boosting returns to wealth, automation exacerbates income disparities (Moll et al., 2022). The information and communication technology (ICT) role in wage inequalities has also been largely studied by the literature that highlights its polarisation effect. In fact, tasks involving non-routine processes and cognitive activities have been complemented by ICT generating a higher demand for high-skilled, higher educated workers at the expense of middle-skilled ones (Michaels et al., 2014).

Despite the richness of studies on the wage distribution effects among occupational groups deriving from the adoption of ICTs and robots, little is known about the impact of the adoption of the new digital technologies, with a few very recent exceptions (Cirillo et al., 2021; Fossen & Sorgner, 2022).

Beside the novelty of the technologies, this gap in the literature is also motivated by the complexity of the phenomenon both on the conceptual and measurement grounds. Digitalisation, in fact, has to be meant (and measured) not simply as the adoption of a specific technology, as in the case of the upgraded ICTs, which characterised the computerisation revolution of the 1990s, but as that bunch of technologies (e.g., cloud, AI, digital networks, etc.) necessary for the transition towards what some authors have defined as the *digital service economy*. This label refers to an economy based on a sprawling range of businesses enabled by digital platforms and leading to a redesign of the boundaries between products and services (in favour of the latter), with deep effects on business opportunities, competition dynamics and, consequently, occupational outcomes and wage redistribution (Capello et al., 2022b). Importantly, digitalisation can expand the task set at the top of the skill distribution spectrum, widening the labour demand for high-skilled jobs (Acemoglu & Restrepo, 2018; Fossen & Sorgner, 2022). Such an expansion is typically associated with a parallel widening of low-skilled (consumer) service jobs, also known as the 'gig-economy' phenomenon (Gokan et al., 2022), therefore leading to a general reinstatement effect. Although service jobs are, in principle, relatively less impacted by (if not neutral to) technological advances, the combination of consumer preferences for service output variety, the limited substitutability of the output of service jobs and the non-neutrality of technological progress can make them expand too (Autor, 2022; Autor & Dorn, 2013; Goos et al., 2018). However, the final effect on the occupational groups wage bill share remains doubtful, since the new technologies can create new jobs without a parallel expansion of their productivity (Autor & Salomons, 2018). In fact, whether the reinstatement effect pushed by the diffusion of the new digital technologies can produce a narrowing or a widening of wage inequalities among occupational groups is subject to the relative balance between the productivity and the reinstatement effect of digitalisation for the different groups of occupations. If the productivity effect is larger than the reinstatement effect for the high-skilled while the reinstatement effect is greater than the productivity effect for the low-skilled, then wage inequalities can be expected to raise rather than to narrow, despite the increase of labour demand and of the aggregate wage bill of each group.[3]

Importantly, labour markets can react differently to the adoption of the new digital technologies. Whereas most of the literature has implicitly assumed that technology adoption effects take place irrespective of *where* the new technologies are adopted, the operation of agglomeration economies can lead to large spatial heterogeneity in the actual labour market outcomes. Specifically, because of the operation of urbanisation economies stemming from the presence of a large mix of sectors and occupations and a consequent highly differentiated urban labour force (Duranton & Puga, 2020), urban settings are likely to experience enhanced productivity and reinstatement effects deriving from the adoption of the new digital technologies, for both low- and high-skilled workers and, consequently, can be more exposed than other types of settings to a rise in wage inequalities. In fact, on the one hand, cities are the most digital technology-intensive *loci*. As highlighted in Forman et al. (2005), urban areas provide opportunities to access essential knowledge to innovative activity (Forman et al., 2005) and become a source of sustainable competitive advantage (Porter, 1998). Cities are dynamic hubs that drive innovation and ways of doing business. Social interactions among innovators further fuel learning, creativity and success. As innovators cluster together, they attract more talent, investment and high-quality jobs, reinforcing the city's economic appeal (Moretti, 2014). On the other hand, the highly diversified urban labour markets might absorb the composition effects of digital technologies on both low-skilled and high-skilled occupations. The reallocation of automation-displaced workers, generally mid- and low-skilled, manual and routine manufacturing ones, into low-skilled service jobs[4] (i.e., the composition effects as defined in Acemoglu & Restrepo, 2019) can in fact produce *ripple effects*. Displaced workers might compete against others for non-automated tasks and jobs, bidding down wages and spreading automation's effects to sectors with different labour intensities. More generally, and especially within cities, the diffusion of the new technologies can favour a limited élite of high-skilled and well-paid jobs at the expense of many (mostly) low-skilled and low-wage jobs (Autor, 2022). Cities, therefore, can play a role as *catalysts of inequalities*.

The spatial heterogeneity of the link between digitalisation and inequalities, however, remains an area that requires further exploration. Several studies have, in fact, discussed inequalities among urban and non-urban areas (Moretti, 2013) as well as the potentially strategic role of digitalisation to reduce urban-rural disparities by alleviating poverty in rural contexts (Fu et al., 2024). However, no consensus has been achieved on whether digitalisation narrows inequalities or creates new divides (Fang et al., 2024). While it offers socio-economic advancement opportunities, digitalisation also raises concerns about the digital divide, potentially deepening urban-rural disparities and fostering social polarisation (Wang et al., 2021).

Unlike previous studies, this paper does not focus on the role of digitalisation in mitigating or strengthening urban vs non-urban inequalities but rather it aims at contrasting the effects of digitalisation among occupational groups wage inequalities across different types of settlements (i.e., urban vs non-urban). In other words, the paper studies whether the same relationship (i.e., digitalisation and wage inequalities among occupational groups) operates differently across areas characterised by different settlement structures, an aspect rarely addressed by the existing literature. Fossen and Sorgner (2022) report about a robustness check controlling for the metropolitan location of workers. Autor and Dorn (2013) as well as Acemoglu and Restrepo (2020) have addressed, respectively, the role of ICTs and robot adoption for the labour market within urban environments. None of these studies, though, *contrast the effects across urban vs non-urban settlements*.

This paper, then, attempts to overcome such gaps by analysing the effects of digitalisation on wage inequalities among occupational groups in different territorial settings. It does so by conceptually elaborating on the difference between the new digital technologies and the past waves of computerisation and robotisation in terms of employment and wage bill distribution among occupational groups, and by explaining why these effects are primarily an urban phenomenon. On the empirical grounds, the analysis is run by comparing urban vs. non-urban settings in Italy (NUTS3), with urban areas being expected to experience more profound impacts on wage inequalities among occupations from the adoption of the new digital technologies. Applying an ordinary least squares (OLS) estimation method in a cross-sectional framework, the paper highlights that digitalisation is associated with important compositional effects leading to a concentration of wealth within high-skilled occupations primarily in metropolitan areas, and to both a displacement and a negative productivity effect for low-skilled workers particularly in non-urban contexts.

In detail, Section 2 sets out the conceptual framework. Section 3 presents the data used to measure the concepts of interest. Section 4 introduces the econometric approach, Section 5 discusses the results and Section 6 concludes.

2. DIGITALISATION, WAGE INEQUALITIES AND THE CITY: CONCEPTUAL FRAMEWORK AND HYPOTHESES

Concerns, if not fear, about the (un)employment impact of the new technologies are not new and have characterised each wave of major technological progress (or technological/industrial revolution). Recently, the debate has been reignited by the works of Brynjolfsson and McAfee (2014) and, especially, Frey and Osborne (2017), highlighting gloomy prospects for the number and the quality of jobs because of the spread of the new technologies, and offering a resurgence for automation anxiety (Akst, 2013; Autor, 2015a).

Despite the fact that the early projections by Frey and Osborne (2017) have been disproved (Arntz et al., 2018), the crucial, but still largely unanswered, question is whether this time is different with respect to the previous technological waves (Balsmeier & Woerter, 2019). The reply to this question remains compelling, though challenging on both conceptual and empirical grounds, in that it allows the understanding of not only the magnitude of the employment creation (i.e., reinstatement effect) vs. destruction effect (i.e., displacement) of digital technologies but also, and possibly even more importantly, its distributive outcomes among different occupational categories, i.e., their impact on wage inequalities. By wage inequalities this paper refers to the uneven wage bill distribution among occupational groups with a few (high-skilled and high-paid) workers earning a large portion of the total wage bill (low employment share at high wage level) and most (low-skilled and low-paid) ones earning a small portion (high employment share at low wage level). More specifically, the skill- and task-biased technological change literature suggest an increase in productivity of skilled labour led by the adoption of digital technologies. Simultaneously, an expansion of the tasks and jobs set (i.e., reinstatement) is expected to stem directly and indirectly from digitalisation, especially enlarging the unskilled labour force. Even though the aggregate effects of these two mechanisms seem to favour an increase of the aggregate labour share and wage bill, between-group wage inequalities might increase (Autor, 2022).

The previous industrial revolutions (i.e., ICTs in the 1990s and enhanced automation, especially of the manufacturing environment from the 2000s and increasingly from the 2010s[5]) have been each characterised by distinctive general-purpose technologies presenting a different capacity to complement or to replace human labour with different types of skills and in different types of tasks (Table 1). On the one hand, the ICTs revolution originally presented a strong complementarity with high-skilled jobs, pushing upward their productivity and wages together with their demand and generating optimism about the upskilling potential and the flattening of inequalities (Acemoglu, 1998). However, the progressive erosion of mid-skilled routine occupations has produced an increasing polarisation of employment and wages, ultimately widening wage inequalities in the labour market (Autor et al., 2003; Autor & Dorn, 2013). On the other hand, the automation trend, especially in the form of robotisation within the manufacturing environment, characterising the last couple of decades has highlighted once more the vulnerability of low-skilled occupations, their high substitutability and the compression of their wage bill share, leading again to enlarged inequalities (Acemoglu & Restrepo, 2018, 2020).

However, technologies can have a double nature, entailing not only tasks (and jobs) displacement but also tasks (and jobs) reinstatement (Acemoglu & Restrepo, 2019; Autor et al., 2022); in this respect, recent digital technologies present a very different nature compared with automation

Table 1. Effects of different technological revolutions on labour market outcomes.

	ICTs	Automation	Digitalisation
Nature of the technology	a. Complementary to high-skilled (cognitive) jobs b. Substitution of mid-skilled (routine cognitive) jobs	Substitution of low-skilled (routine manual) jobs	a. Complementary to high-skilled (non-routine cognitive) jobs b. Labour-augmenting
Employment share	a. High-skilled jobs reinstatement (upskilling) b. Routine jobs displacement (polarisation)	Low-skilled jobs displacement (upskilling)	Low-skilled and high-skilled jobs reinstatement (both job upskilling and deskilling)
Wage bill share	a. Increase of high-skilled wage bill share b. Increase of both high- and low-skilled wage bill shares	Decrease of low-skilled wage bill share	Increase of both high- and low-skilled wage bill share
Wage inequalities	a. Wage inequalities increase b. Wage inequalities increase	Wage inequalities increase	Uncertain – to be tested empirically
	Autor et al., 2003; Michaels et al., 2014	Acemoglu & Restrepo, 2019	Autor & Salomons, 2018; Autor et al., 2022

ones. In fact, despite alarming views on their displacement potential, several authors remark their capacity to expand the task set at the top and the bottom of the skill distribution spectrum, with positive effects on labour demand and the wage bill (Acemoglu & Restrepo, 2019; Autor et al., 2022; Fossen & Sorgner, 2022). This effect, therefore, could act like a powerful mechanism to counter the rise of wage inequalities that, in the past, derived from each major wave of technological progress, making empirical exercises necessary to resolve the puzzle. The capacity of generating new tasks and jobs (i.e., reinstatement effect) and the relative productivity of these new jobs (i.e., productivity effects) are therefore crucial to understand whether the new digital technologies can escape from the *inequality curse* associated with past technological revolutions.

The comparison with automation technologies is useful to illustrate this point. Automation technologies, *in primis* the widely documented case of robots (Dauth et al., 2021; Graetz & Michaels, 2018, among many others), produce two concomitant but opposite effects on labour demand (Acemoglu & Restrepo, 2019). The former is one of *displacement* ($\Delta E \downarrow$, where E indicates *Employment*) of existing tasks and (low-skilled) jobs, leading to a reduction of the labour share (Table 2). The latter is an increase in *productivity* of existing tasks and jobs ($\Delta w \uparrow$, where w indicates *wages*), making these technologies *intensive labour-augmenting* (Johnson, 1997) and contributing to the demand for labour in non-automated tasks (Acemoglu & Restrepo, 2019). If the productivity effect is smaller (in absolute terms) than the displacement

Table 2. Effects on wage inequalities: automation vs digitalisation.

	Effect on productivity	Effect on employment	Effect on the wage bill	Effect on wage inequalities among occupational groups
Automation	$\Delta w \uparrow$ intensive labour augmenting	$\Delta E \downarrow$ displacement	$\Delta W \downarrow$ if $\lvert\Delta w\rvert < \lvert\Delta E\rvert$	$\uparrow$
Digitalisation	$\Delta w \uparrow$ extensive labour augmenting	$\Delta E \uparrow$ reinstatement	$\Delta W \uparrow$	$\uparrow$ if $\Delta w_{LS} < \Delta E_{LS}$ but $\Delta w_{HS} > \Delta E_{HS}$

Notes: E = employment, W = wage bill; w = wage; LS = low-skilled; HS = high-skilled.

effect, the outcome is one of a reduction of the labour share and therefore of the wage bill ($\Delta W \downarrow$, where W indicates the wage bill, i.e., w x E) driven by the displacement of low-skilled workers leading to widened wage inequalities (Acemoglu & Restrepo, 2018, 2020).[6] Digital technologies, instead, by generating favourable reinstatement ($\Delta E \uparrow$) and productivity ($\Delta w \uparrow$) effects can, in principle, positively affect both the labour demand and the wage bill (Acemoglu & Restrepo, 2019), being therefore *intensive labour-augmenting* technologies (Johnson, 1997).

Even if at a first glance, the expansion of both the labour demand and the wage bill may look a desirable outcome, this aggregate effect tells little about the relative magnitude of the reinstatement and productivity gains for different groups of workers, and, therefore, for the widening or narrowing of wage inequalities among occupational groups.

Expectedly, new digital technologies expand and/or upgrade the task set at the top of the skill distribution spectrum, e.g., tasks related to the development and the management of increasingly complex equipment and devices (e.g., software and hardware development, mainly in the field of AI and its applications to machine learning, analytics, cyber-security, just to mention a few) but also upgraded tasks (e.g., those related to the maintenance and repair of sophisticated and smart medical equipment). Moreover, as a second order effect, new digital technologies can expand the task set also at the bottom of the skill distribution spectrum especially in (consumer) service jobs (e.g., occupations linked to cosmetology like nail care, or linked to mobility solutions or entertainment) because of multiplier effects from high-skilled jobs to low-skilled ones (Goos et al., 2018; Moretti, 2010), consumer preferences for variety and limited substitutability of most service job outputs (Autor & Dorn, 2013; Gokan et al., 2022).

The reinstatement effects taking place at the top and the bottom of the skill distribution however can be substantially different in size (Autor et al., 2022), and, more importantly, the relative magnitude of the reinstatement effect with respect to the productivity effect can vary among occupational groups, leading to a decoupling of the growth in the number of jobs with respect to productivity (Autor, 2022; Autor & Salomons, 2018; Brynjolfsson & McAfee, 2014).

In fact, if job creation at the bottom of the skill distribution predominantly revolves around reallocation mechanisms making labour move from more productive to less productive labour force segments, subject to downward pressure on wages because of enhanced competition (Autor, 2022; Baumol, 1967; Camagni et al., 2023), the labour reinstatement effect can become substantially larger than the parallel productivity effect, as shown by Autor and Salomons (2018), suggesting a decoupling of productivity growth from any increase in the number of jobs.

Alternatively, if job creation at the top of the skill distribution predominantly involves new specialities mainly characterised by higher productivity and wage levels with respect to existing ones, the consequent reinstatement effect can be significantly smaller than the productivity effect, a desirable outcome *per se* in that it represents an important source of aggregate productivity growth (Acemoglu & Restrepo, 2020; Autor et al., 2022). The result is a higher wage bill share for high-paid workers, with positive consequences also for the aggregate productivity deriving from human capital externalities accruing to local areas (Moretti, 2003).

The combination of these two outcomes (summarised in Table 2), therefore, generates more favourable employment and, especially, wage conditions for high-skilled workers than for low-skilled ones, thus amplifying existing wage inequalities.

These effects, however, are not spatially invariant; urban settings, in fact, are particularly exposed to these side effects of digitalisation, for two main reasons. First, urban settings are unanimously considered the *loci* of new technology adoption; more intense technology adoption can exacerbate inequality effects in cities (Duranton & Puga, 2001). Second, the diversity of urban labour markets fuels the multiplying (recursive) mechanisms linking high-skilled and low-skilled workers. New digital (top-skilled) occupations are likely to flourish in metropolitan areas (Eckert et al., 2020), leading to a surge in demand for consumer services provided by low-skilled workers (Gleaser et al., 2001; Gokan et al., 2022), generating multiplicative effects on less-skilled workers (Gokan et al., 2022; Goos et al., 2018; Moretti, 2010). Top talents enjoy a well-documented urban wage premium (Autor, 2019; Combes et al., 2008, 2012), suggesting that for them the productivity effect is particularly high, possibly higher than the reinstatement effect. However, low-skilled workers are increasingly subject to a downward pressure on wages, spurred further by the tough competition between online and traditional activities (Kenney & Zysman, 2016; Koutsimpogiorgos et al., 2020; Stanford, 2017). Despite a large positive reinstatement effect, therefore, their productivity effect can remain relatively small, and smaller than the reinstatement ones. Together, these effects, triggered by the operation of urbanisation economies (i.e., the size of labour markets and the highly heterogeneous mix of occupations within cities) make urban environments particularly subject to the raise of wage inequalities stemming from the adoption of digital technologies.

This statement has to be proved empirically as detailed in the following sections.

3. FROM CONCEPTUAL DEFINITIONS TO EMPIRICAL MEASUREMENTS

3.1. Measuring digitalisation

The empirical verification of the conceptual approach set out in the previous section rests on the operationalisation of three main concepts: digitalisation, wage inequalities and the city.

Each of these concepts is highly complex and, by nature, multifaceted. The solutions proposed in this paper, therefore, are the outcomes of conceptual reflections and the balance between several arguments.

Starting with digitalisation, its definition and measurement are a challenging goal both because of the multifaceted nature of digitalisation itself and its potentially different manifestations depending on the specific productive or institutional contexts in which it takes place (Calvino et al., 2018; Cirillo et al., 2021).

The specific measure of digital technology adoption used in this paper is the diffusion of cloud services in Italian firms, namely the share of firms using cloud services in a NUTS3 region. This choice derives from several considerations, inspired by the final goal of obtaining an indicator able to capture at least some of the novel aspects of the present digitalisation with respect to the past ICTs revolution, largely based on the endowment of ICTs equipment and/or infrastructure and/or personnel (Calvino et al., 2018; e.g., Autor et al., 2003; Biagi & Falk, 2017; Cirillo et al., 2021; Goos et al., 2014). In this respect, the adoption of cloud computing services represents a proxy for the general shift to online/digital modes of doing business. In fact, exploiting the internet for data storage, networking, sharing of databases for supporting and improving every-day-activities represents a business transformation towards digital (automated) planning and management practices. Furthermore, cloud computing represents a strategic asset that supports and acts in synergy with the most disruptive ongoing technological innovation, i.e., AI. In fact, the cloud provides the necessary infrastructure and tools to support the development and delivery of AI generated content. The cloud can also enable smooth integration of AI solutions with existing internal systems and workflows (Jacobides et al., 2021). Therefore, the share of firms using cloud services implicitly takes into consideration the scalability potential of this technology that might serve as the basis for a full range of AI's capabilities.

Importantly, the use of cloud services as an indicator of digital technology adoption is preferred to those based on patent data in advanced digital technologies (e.g., AI) or those based on the use of automation technologies (i.e., robot adoption), which are both strongly sector specific. Patents do represent cutting-edge inventions but do not always go in tandem with technology adoption and are especially low in services (Tether, 2005).[7] On the other hand, robot adoption captures the automation process primarily in the manufacturing environment (Acemoglu & Restrepo, 2020; Büchi et al., 2020). The sector-specific nature of these indicators makes them not particularly suitable in the present setting, in which both the manufacturing and service sectors are taken into consideration.[8]

Admittedly, the use of cloud computing services captures only a portion of the (many) advanced technologies currently under development and in expanding use; yet they do still represent an area of major technological advances, being also crucial to the development of the smart fabric and Internet-of-Things (EPO, 2020). Moreover, data on the use of cloud services offers the best balance between data availability (especially in terms of temporal coverage) and accuracy of the measure for our purposes.[9] For example, data on the use of AI or big data presents significant temporal constraints (e.g., EUROSTAT (the statistical office of the European Union) national data on AI starts from 2018 with sizeable gaps).[10]

Data on the use of cloud service derives from ISTAT (Italian National Institute of Statistics), more precisely from the *Survey on Information and Communication technologies in enterprises (ICT)*.[11] This survey – one of the major sources of data for the Digital Agenda Scoreboard used to measure the progress of the European digital economy by the European Commission – collects data on the use of digital technologies at the firm level, for companies with at least 10 employees active in industry and in non-financial services from 2014 to 2019[12] with a fine regional (i.e., NUTS2 level) breakdown.

The approach adopted in order to apportion the share of firms adopting cloud computing services from the NUTS2 level to the NUTS3 one follows Camagni et al. (2023) in line with the literature (e.g., Acemoglu & Restrepo, 2020). Specifically, two weights have being applied accounting for the NUTS3 sectoral specialisation and digital infrastructure, with both expected to raise the intensity of use of digital technologies.[13]

$$\begin{aligned} \mathrm{SHARE\_CLOUD}_{\mathrm{NUTS3,t}} = {} & [(1/2)\mathrm{x}\ \mathrm{w\_SPEC}_{\mathrm{NUTS3,t}} + (1/2)\mathrm{x}\ \mathrm{w\_BB}_{\mathrm{NUTS3,t}}] \\ & \mathrm{x}\ \mathrm{SHARE\_CLOUD}_{\mathrm{NUTS2,t}} \end{aligned} \tag{1}$$

The first weight, $\mathrm{w\_SPEC}_{\mathrm{NUTS3,t}}$, follows the expectation that the share of firms that adopts cloud computing services is linked with the specialisation in the sectors included in the survey, i.e., provinces (NUTS3) more specialised in the survey sectors contribute more to regional (NUTS2) cloud services adoption, and thus have a greater share of firms adopting cloud services (the use of this weight is common in the scientific literature, see for instance Acemoglu & Restrepo, 2020). NUTS3 sectoral specialisation has been computed as the location quotient by applying the usual formula based on employment data sourced from ISTAT.

$$\mathrm{w\_SPEC}_{\mathrm{p,t}} = (Emp_{p,s,t}/Emp_{p,t})/(Emp_{r,s,t}/Emp_{r,t}) \tag{2}$$

where Emp stands for the number of employees, p the province (NUTS3), r the region (NUTS2), s the sectors included in the survey and t the year.

The second weight, $w\_BB_{nuts3,t}$, is the NUTS3 share of households with broadband access with respect to the regional share. This weight follows the expectation that the adoption of cloud computing services is more widespread in provinces characterised by the presence of an adequate digital infrastructure and a more digitalised population, i.e., in regions more prone to adopt new technologies.[14] This weight is computed as the location quotient of the households with broadband access (source: ISTAT, 2011 census).

$$w\_BB_{p,t} = (HH\_BB_{p,t,}/HH_{p,t})/(HH\_BB_{r,t}/HH_{r,t}) \tag{3}$$

where HH stands for the number of households, HH_BB for the number of households with broadband connection, p the province (NUTS3), r the region (NUTS2) and t the year.

Finally, we calculated the average of the yearly cloud technology adoption data over time (specifically, the average of the 2014, 2015 and 2016 yearly data) to mitigate potential fluctuations associated with any single year.

3.2. Measuring wage inequalities among occupational groups

The concept of inequality has many facets (Autor, 2019, 2022) and inequalities may be measured among occupational groups, by education or gender or between top versus bottom income individuals. Following the discussion in Section 2, the focus here is on wage inequalities among occupational groups characterised by different skill intensity (Michaels et al., 2014). Specifically, the role of digital technologies for occupational groups' wage inequalities is examined by comparing the effects on (skill-specific) employment share variation (interpreted as the displacement/reinstatement effect) and the ones on (skill-specific) wage bill share variation (interpreted as productivity effect).

Data on employment and wages by occupational groups with a territorial (i.e., NUTS3 level) breakdown is obtained from the *Labour Force Survey (Rilevazione sulle forze lavoro – RFL)*, which collects individual level data on employment conditions from 2009 to 2020 quarterly covering the employment status, the sector, the occupation, the education, the contractual arrangement, the wage and the NUTS3 region of residence of each respondent.[15] Specifically, individual level data on wages (i.e., last month's net salary excluding other monthly salaries – 13th, 14th, etc. – and ancillary items not regularly received every month – annual productivity bonuses, unusual overtime, etc.) has been aggregated by occupational groups (i.e., high-, mid- and low-skilled occupations, as defined by ISTAT)[16], and by NUTS3 region. More in detail, high-skilled occupations include legislators, entrepreneurs and senior management, and intellectual, scientific and high specialised occupations, corresponding to the ISCO (International Standard Classification of Occupations) macro-groups of managers and professionals (ISCO codes 1 and 2). Low-skilled occupations include non-qualified occupations, corresponding to the ISCO macro-group of elementary occupations (ISCO code 9). Mid-skilled occupations include all remaining ones, ranging from technical occupations (ISCO code 3) to executive occupations in office work (ISCO code 4), from qualified occupations in commercial activities and services (ISCO code 5), to craftsmen, specialised workers and farmers (ISCO codes 6 and 7) and finally plant operators, machine operators and vehicle drivers (ISCO code 8).[17]

The groups of occupations have been based on skills, rather than on tasks, for a number of reasons. Firstly, the need of our empirical analysis was in fact to have a clear distinction between low-paid and high-paid jobs that could directly reflect differences in productivity levels among occupational groups. The distinction between low- and high-skilled occupation is for this purpose sufficient. Secondly, this choice also allows overcoming the unavoidably subjective separation between high-paid tasks and low-paid ones, since a common definition in this respect has not yet been reached in the literature. If cognitive tasks can be generally assigned to a high-paid group, and the manual ones to a low-paid one, the routine and nonroutine tasks suffer from an unclear distinction, as they are in general non-mutually exclusive with respect to cognitive and manual ones. Thirdly, in the institutional context of our empirical analysis (Italy) wages are decided through national contracts that differ by skills rather than by tasks. In fact, two occupations of the same skill level but with a different mix of technology substitutable tasks can end up with a similar wage level.

Following Autor (2019), the variation in the share of employment and wages out of the total wage-bill by occupational group is used as a measure of the evolution of wage inequalities amongoccupational groups. Specifically, the variation was computed over the period 2012 and 2019, deflating 2019 wages to the initial year (i.e., 2012). The choice of this specific timespan balances the availability of data measuring wages and digital technology. On the one hand, the Labour Force Survey provides *net* wages data until 2020 (only for the first two quarters) and *gross* wages data from 2021 onwards. On the other hand, data measuring the diffusion of cloud services in Italian firms are available starting from 2014. Besides data availability restrictions, this timespan allows the exclusion of the periods of the 2008–2012 financial crisis and the outbreak of COVID-19 pandemics. Furthermore, the digital technology examined in the paper had not been much developed before this timeframe, making it difficult to analyse its relationship with occupations and wages in previous years.

3.3. The concept of city and its measurement

The operationalisation of the concept of city is controversial in the literature. From the conceptual perspective, the city is a clear and well-accepted economic archetype characterised by the operation of agglomeration economies, thus with self-evident differences with respect to the non-city. From the empirical perspective, instead, the literature has amply discussed how a city and its physical (and economic) boundaries can be identified, i.e., where an agglomeration is a city and where a city ends and a non-city starts (Camagni et al., 2023; Westlund & Borseková, 2025). Consequently, alternative measurement strategies have been proposed depending on the empirical setting under examination. This paper follows a solid tradition and uses the administrative approach and the NUTS classification to identify cities (see, among others, Camagni et al., 2023; Capello et al., 2023; Ciccone, 2002; Di Liberto & Sideri, 2015; Guiso et al., 2004; Perucca, 2014); the administrative approach is also followed by EUROSTAT that adopts a classification of metropolitan areas based on NUTS3 regions.[18]

The alternative option, based on the functional approach (i.e., the identification of functional urban areas (FUA) or of local labour markets (LLS)) instead, is not particularly appropriate in the Italian setting. On the one hand, LLS is a too small spatial unit to capture the operation of urbanisation economies. For example, Milan NUTS3 contains five LLS, Rome contains seven LLS, Turin contains eight LLS. On the other hand, the list of FUAs proposed by EUROSTAT overlaps almost perfectly with NUTS3 regions while that proposed by ISTAT is based on 83 FUAs (identified by aggregating LLSs), very similar to the 106 NUTS3 regions analysed in this work (Camagni et al., 2023; Capello et al., 2022a; Capello et al., 2023).

The similarity between the two approaches, the stability of the NUTS3 classification in the period examined, and the advantages of using NUTS3 regions in terms of data collection for the other variables used in the econometric analysis enable the conclusion that using NUTS3 regions as a measure of cities is appropriate in the present context. Specifically, cities are identified as the 25% largest NUTS3 regions, a threshold corresponding to a population greater than 600,000 inhabitants.

4. THE ECONOMETRIC FRAMEWORK

Following Michaels et al. (2014), the labour market and distributive outcomes of digital technologies adoption among different occupational categories are analysed in a cross-sectional estimation framework[19] with the employment and wage bill share of each occupational group (i.e., high-skilled, mid-skilled and low-skilled occupations) as dependent variables, as summarised in Equations (4) and (5):

$$\Delta \text{employment share}_{o,p} = \alpha + \beta_1 \text{digitalisation}_p + \beta_2 \text{digitalisation}_p \text{x metropolitan area}_p + \beta_3 \text{wage bill share}_{o,p} + \beta_4 X_p + \beta_5 Z_{o,\,p} + \text{macroarea FE} + \varepsilon \quad (4)$$

$$\Delta \text{wage bill share}_{o,p} = \alpha + \beta_1 \text{digitalisation}_p + \beta_2 \text{digitalisation}_p \text{x metropolitan area}_p + \beta_3 \text{employment share}_{o,\,p} + \beta_4 X_p + \beta_5 Z_{o,\,p} + \text{macroarea FE} + \varepsilon \quad (5)$$

Specifically, *Δ employment share*$_{o,\,p}$ and *Δ wage bill share*$_{o,\,p}$ refers to the difference between 2012 and 2019 of the employment and wage bill share of each occupational group *o* over, respectively, the total employment and the wage-bill in each NUTS3 province *p*. *Digitalisation* represents the explanatory variable of interest also in its interaction with the dummy for *metropolitan area*; X_p *and* $Z_{o,p}$ includes a set of standard control variables (described in more detail below) with either a provincial or both a provincial and occupational breakdown, respectively. Regressions have been estimated through an OLS estimation with heteroskedasticity-robust standard errors.[20]

Running parallel regressions for each occupational group allows comparing the evolution of their respective employment and wage bill shares; inequalities are expected to increase when digitalisation is linked to an increase of high-skilled wage bill share greater than the respective employment share and, concurrently, to a low-skilled employment share increase greater than the respective wage bill share.

The main variable of interest is *digitalisation* which is included at the NUTS3 level (i.e., it is not specific of each occupational group). Following the discussion in Section 2, digitalisation is expected to generate a *positive but unbalanced productivity effect*, favouring especially high-skilled occupations, experiencing a larger productivity effect than a reinstatement effect, while low-skilled occupations are expected to experience a larger reinstatement effect than the respective productivity effect, all this exacerbating inequalities among occupational groups.

Equation (4) estimates employment share variation of each occupational group controlling for the respective wage bill share (i.e., keeping constant the *productivity effect*). This allows interpreting the change in each occupational group *employment share* due to any explanatory variable and primarily digitalisation as a *reinstatement effect*, thus disentangling the productivity effect from the reinstatement one. Importantly, the reinstatement effect exists in the case of an expansion of the employment share of a specific occupational group in response to increases in *digitalisation*. On the contrary, a displacement effect exists in the case of a decrease of the employment share in response to increases in *digitalisation*.

Equation (5) estimates the wage bill share variation of each occupational group controlling for the share of employment of each group (i.e., keeping constant the *reinstatement effect*). Importantly, the productivity effect is positive in the case of an expansion of the wage bill share of a specific occupational group in response to increases in *digitalisation*, suggesting a labour augmenting effect with a constant employment share. The productivity effect is instead negative in the case of a decrease of the wage bill share in response to increases in *digitalisation*; keeping the occupational group employment share constant, a negative productivity effect suggests an impoverishment of that occupational group.

Moreover, the interaction of the digitalisation variable with the dummy *metropolitan area*$_p$, flagging the top 25% most populous NUTS3 regions, enables highlighting the role of different territorial settings in influencing the nexus between the adoption of digital technologies and wage inequalities among occupational groups specifically contrasting urban and non-urban areas.

Finally, a set of control variables (X_p and $Z_{o,p}$) is included, consistent with the existing literature (Acemoglu & Restrepo, 2020; Dauth et al., 2021), some with both a provincial and occupational breakdown ($Z_{o,p}$), and all computed from individual level microdata provided by Labour Force Survey – RFL. In detail, age, female employment share and educational attainment level respectively account for the potential higher wages of older employees, gender wage inequality and higher wages associated with higher educational attainment levels; these variables are included with both a provincial and occupational breakdown. On the other hand, the activity rate variation and the sectoral composition (with a NUTS3 but not an occupational breakdown) are included to consider both the evolution of the labour market and the economic fabric of each region. All variables refer to 2011 in the attempt to better respect a causality nexus between explanatory and dependent variables. Finally, macro-area (i.e., NUTS1) fixed effects are included to consider potential differences in the labour market dynamics across northern, central and southern Italian regions.

Variables description and sources are displayed in Table 3.

As a first step, estimates have been obtained by ordinary least squares (OLS) with robust standard errors. To boost confidence in the results, estimates have been next obtained by two-stage least squares (2SLS) instrumental variables (IV), following an approach inspired by the one

Table 3. Variables description.

Variable	Description	Data source
Inequalities by occupational group	Occupation-specific employment share difference between 2012 and 2019 Occupation-specific wage bill share difference between 2012 and 2019	ISTAT – Labour Force Survey – RFL – Microdata
Digitalisation (NUTS3)	Share of firms using cloud computing services (average between 2014, 2015 and 2016)	ISTAT – Survey on Information and Communication technologies in enterprises (ICT)
Metropolitan areas (NUTS3)	Dummy = 1 if the province is in the 25% largest NUTS3 regions	EUROSTAT
Employment share by occupational group	Employment share in each occupational class in 2011	ISTAT – Labour Force Survey – RFL – Microdata
Age by occupational group	Share of employment aged under 49 in 2011	ISTAT – Labour Force Survey – RFL – Microdata
Female employment by occupational group	Female employment share in 2011	ISTAT – Labour Force Survey – RFL – Microdata
Educational attainment level by occupational group	Share of employment with tertiary education in 2011	ISTAT – Labour Force Survey – RFL – Microdata
Activity rate variation (NUTS3)	Growth rate of the ratio between the number of active persons and the total population between 2009 and 2011	ISTAT
Sectoral composition (NUTS3)	– Employment share in agriculture in 2011 – Employment share in manufacturing in 2011 – Employment share in public administration in 2011	ISTAT

introduced by Acemoglu and Restrepo (2020), aimed at exploiting the exogenous component of technology adoption, driven by the technological frontier (as proxied by trends in other advanced economies). This approach allows the isolation of the technology adoption variable from potentially endogenous trends associated with other industry-level or aggregate developments in the Italian economy that may also be correlated with technology adoption, thus generating an omitted-variable bias. Accordingly, the regional (NUTS2) share of firms using cloud computing services has been instrumental by having, as reference, the average share of firms using cloud services across EU27 + UK countries. Specifically, for each year t, the regional (NUTS2) share of firms using cloud computing services with respect to the Italian share, i.e., the location quotient, was obtained as follows:

$$\mathrm{SHARE\_CLOUD}_{\mathrm{NUTS2/NUTS0,t}} = (\mathrm{SHARE\_CLOUD}_{\mathrm{NUTS2,t}} / \ \mathrm{SHARE\_CLOUD}_{\mathrm{NUTS0,t}}) \tag{6}$$

Next, the denominator has been replaced with the EU27 + UK average, and, by rearranging the terms, the new value for the share of firms using cloud computing at NUTS2 level was obtained. Finally, the apportionment of the NUTS2 level indicator to the NUTS3 level followed the same approach described in Equations (1) to (3).

Given the consistency of results and the interpretation of the IV diagnostics[21], the following comment is based on OLS estimates.

Two additional robustness checks were implemented, yielding qualitatively comparable results. Firstly, progressively more restrictive population thresholds for the identification of cities were applied, namely the 20% most populous NUTS3 regions, the 15% ones (i.e., administrative metropolitan areas) and the top 10% ones. Secondly, the use of alternative time spans for the measurement of the dependent variables (i.e., 2013–2019 changes or 2014–2019 changes) were estimated. All these tests yielded qualitatively comparable results.

5. RESULTS AND DISCUSSION

Table 4 reports the chief results obtained by estimating Equations (4) and (5) for each occupational group, while the complete estimation results are reported in the Appendix in the online supplemental data. Specifically, a positive (negative) sign indicates a statistically significant coefficient of the digitalisation variable on employment and wage bill shares difference, representing respectively the reinstatement and productivity effects. In detail, Table 4 shows the marginal effects of the digitalisation variable computed for metropolitan and non-metropolitan areas taking into consideration its interaction with the metropolitan area dummy on employment and wage bill shares variations.

For facilitating visualisation and interpretation, Figures 1 and 2 plot these marginal effects (when statistically significant) distinguishing metropolitan from non-metropolitan areas.

Figures 1 and 2 clearly highlight that digitalisation appears to hit both employment and wage distribution among occupational groups. Generally, the employment and wage bill share variation in response to digitalisation go in parallel but with imbalances among occupational groups and territorial settings; this heterogeneity in outcomes leads to an increase in inequalities, especially in metropolitan areas.

Specifically, in metropolitan contexts, the employment and wage bill shares of mid-skilled occupations are negatively associated with digitalisation while the employment and wage bill shares of high-skilled occupations are positively linked with digitalisation. These results are, to a certain extent, consistent with the polarisation effect frequently documented as an outcome of the diffusion of computer technologies (Autor & Dorn, 2013). However, for mid-skilled occupations, the marginal effects of digitalisation on employment and wage bill shares are comparable

Table 4. Reinstatement and productivity effects for metropolitan and non-metropolitan areas.

Dependent variable:	Low-skilled occupations	Mid-skilled occupations	High-skilled occupations
Reinstatement effect (Digitalisation on employment share variation 2012–2019)			
Metropolitan areas	−0.112	−0.346**	0.406**
	(0.168)	(0.114)	(0.133)
Non-metropolitan Areas	−0.238***	0.188***	0.018
	(0.052)	(0.047)	(0.041)
Productivity effect (Digitalisation on wage bill share variation 2012–2019)			
Metropolitan areas	−0.318	−0.434**	0.592**
	(0.227)	(0.169)	(0.264)
Non-metropolitan Areas	−0.259***	0.276***	−0.592
	(0.061)	(0.073)	(0.264)

Notes: ***$p<0.01$, **$p<0.05$.

in terms of magnitude, with a relatively greater effect on wages. Taken together, these results suggest that digitalisation is not simply associated with a contraction of mid-skilled occupation employment share, but also with an impoverishment of this occupational group: the wage bill share decreases more than the employment share, remarking that the productivity effect is larger in absolute terms than the displacement effect, and that on average mid-skilled employees earn less. However, it is important to note that mid-skilled workers still gain an urban wage premium, earning higher salaries in metropolitan areas compared to non-metropolitan areas.[22]

For high-skilled occupations, instead, digitalisation has a positive association with both employment and wage bill shares, i.e., the productivity effect is positive and associated with a reinstatement effect. Importantly, the productivity effect is stronger than the reinstatement

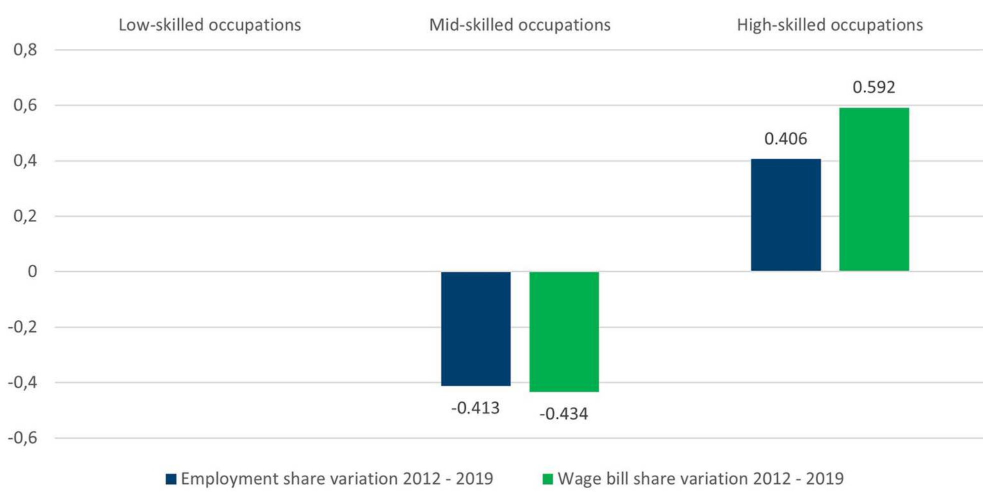

Figure 1. Reinstatement and productivity effects in metropolitan areas by occupational group (2012–2019).

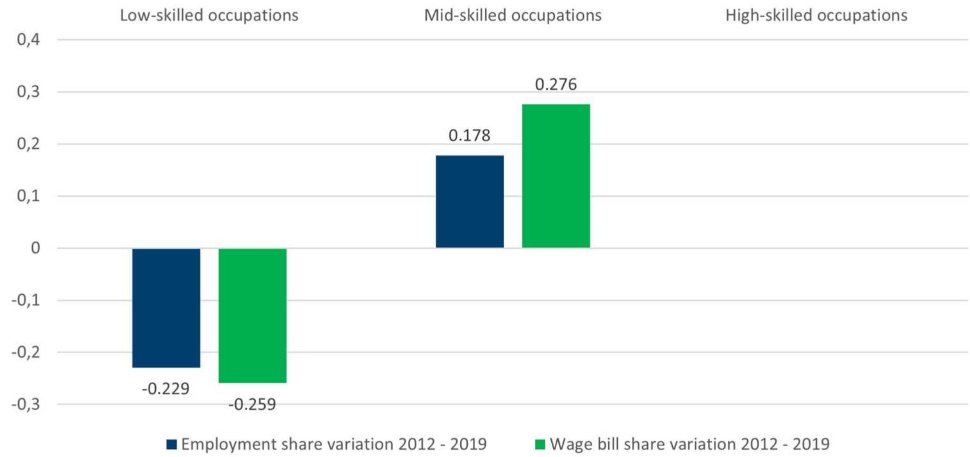

Figure 2. Reinstatement and productivity effects in non-metropolitan areas by occupational group (2012–2019).

effect, in that the marginal effect for the wage bill share is far greater than that for the employment share. This result suggests that on average high-skilled employees earn more, and that digitalisation is associated with an extensive labour augmenting effect. For high-skilled occupations, then, the results are in line with the hypotheses presented in Table 2 (Section 2). These findings align with recent literature examining the relationship between digitalisation and inequalities, using patents in digital technologies and especially AI as a measure of digitalisation (e.g., Bhattacharya et al., 2022). In fact, the available evidence seems to suggest (modest) positive effects in terms of employment growth (Albanesi et al., 2025), especially in the largest and most innovative firms (Damioli et al., 2023), in the most technologically advanced countries and regions (Guarascio et al., 2025) and for skilled and high-income workers (Eloundou et al., 2023; Brynjolfsson et al., 2025). Similarly, Kogan et al. (2023) report that, unlike labour-saving technologies (e.g., robotisation), the effects of labour-augmenting technologies are more heterogenous, disproportionately benefitting white-collar, older and higher-paid workers.

However, low-skilled occupations seem relatively neutral to the effects of digitalisation; this result departs from what was anticipated in Section 2. Possibly, this result may suffer from the high heterogeneity of occupations included in the low-skilled category. While some occupations (e.g., delivery service occupations, frequently associated with the gig economy) can be highly influenced (and hit) by digitalisation, others (and possibly the majority of low-skilled ones) can be left completely unaffected (e.g., caregivers, housekeepers). At present, data limitations and representativeness issues at the territorial level do not allow using a more disaggregated occupational breakdown, which instead could be useful, if not necessary, to unpack the effect of digitalisation. At a superficial look, the neutrality of digitalisation for low-skilled occupations and the upskilling trend associated with the expansion of high-skilled ones may represent a favourable outcome and speak in favour of a reduction of inequalities. Yet, the imbalance between the reinstatement and productivity effects, especially for the high-skilled, suggests that this upskilling trend masks a concentration of wages and, consequently, a widening of wage inequalities in metropolitan areas.

The upskilling trend characterising metropolitan areas takes place also in non-metropolitan ones but shifting low-skilled occupations towards mid-skilled ones, even if high-skilled occupations seem to be neutral to the adoption of digital technologies. Digitalisation is associated with a contraction of both the employment and the wage bill shares of low-skilled occupations, suggesting that the productivity effect is larger (in absolute terms) than the displacement effect and, on average, low-skilled workers become poorer. However, mid-skilled occupations benefit the most from digitalisation, which is positively and significantly related with an increase of their employment and wage bill shares. With the latter larger than the former (i.e., the productivity effect is stronger than the reinstatement effect), mid-skilled workers become wealthier, on average.[23] Also in this case, the imbalance between the reinstatement and productivity effects, especially for the mid-skilled, suggests that the upskilling trend masks a concentration of wages and, consequently, a widening of wage inequalities. Quite interestingly, however, the magnitude of the effects in non-metropolitan areas is far smaller than in metropolitan ones, suggesting that the rise of inequalities is predominantly a metropolitan phenomenon, as discussed in Section 2 and consistent with Breau et al. (2014), indicating higher inequalities in more innovative and more technology-intensive cities.

In conclusion, these findings highlight that digitalisation is linked with a generalised upskilling trend, similar to the initial stages of the previous computerisation era (Acemoglu, 1998); however, relevant compositional effects are in place, leading to a concentration of wealth within high-skilled occupations, primarily in metropolitan areas. Contrary to the expectations, data does not show a significant link between digitalisation and low-skilled occupation employment and wage bill shares in metropolitan areas. As argued above, the high heterogeneity of this occupational group, coupled with a decrease of their respective employment share in both metropolitan and non-metropolitan areas,[24] can prevent uncovering the hypothesised effects, being the low-skilled occupational group probably predominantly made of jobs with high substitutability (in non-metropolitan areas), if not neutral (in metropolitan setting) to digitalisation.

6. CONCLUSIONS

The results of our empirical analysis suggest that the automation anxiety that is back in newspapers and public opinion as the big challenge of the digitalisation era (Autor, 2015b) is not fully consistent with the reality. Digital advances seem not to create the mass unemployment that many fear. The reading of the evidence confirms that digitalisation may lead to reinstatement effects. However, this is true for high-skilled workers, enjoying a decisive productivity effect. Instead, for a substantial subset of workers, digitalisation has either depressed wages or/and displaced workers. This is the case of middle-skilled and low-skilled jobs (respectively in metropolitan and non-metropolitan areas).

Instead, the worrying aspect of the digital transition, reinforced by this study, is that digital technologies are not welfare improving technologies, suggesting that the concerns put forward in the literature are in this case well-placed. New digital technologies exacerbate inequalities among occupational groups in terms of wage bill share distribution. But the story appears even more problematic, in that the worsening of inequalities among occupational groups is not space neutral. Digitalisation enables cities to enjoy a high-skilled labour augmenting effect, with a productivity effect prevailing over the reinstatement effect. At the same time, cities experience a reduction in the productivity effect and a displacement effect of middle-skilled workers. All this leads to a polarisation of the urban community between less middle-skilled workers earning much less and a few more high-skilled workers earning much more. Urban contexts are therefore deemed to play a role as catalyst of inequalities among occupational groups.

The results of this paper are a reminder that the digital transition has to be accompanied with policy actions in the labour market, so as to limit inequalities otherwise produced. On the one hand, policies targeted at innovation should take into consideration the consequent effects on inequalities. For instance, stronger patent protection or higher research and development (R&D) subsidies might boost economic growth while raising real interest rates and increasing asset income, with detrimental consequences on inequalities and widening gaps between asset-rich and asset-poor social groups. Additionally, policies enhancing asset value may increase monopolistic profits, further amplifying income inequality (Chu & Cozzi, 2018). As also highlighted by the Organisation for Economic Co-operation and Development (OECD) (2013, 2014), public policies, such as patent policies, are one of the main elements to influence the relationships between technology and labour. Special attention should be devoted to the role of incentives for technological change and the corresponding effects on the compensation structure of firms, with consequent implications on wage inequalities.

On the other hand, these concerns related to the consequences of innovation policies are especially evident in urban areas, where inequalities naturally accelerate. A long-term commitment to increasing substantially the share of individuals achieving a higher level of education can be an appropriate public policy response to the phenomenon of increasing inequality (Autor, 2015a), with a clear role for institutions in determining the acquisition of technical skills in the workforce. Yet, with all 'this is more easily written than done effectively' (Johnson, 1997, p. 53).

This paper is a first study on the spatial differences in inequalities among occupational groups generated by digitalisation. Limitations, especially related to data availability, can leave space for further analysis. For example, more detailed and precise spatial data on the adoption of different digital technologies and on specific low-skilled category of workers would allow a more sophisticated analysis on the various effects of different forms of digitalisation on wage inequalities. This is an interesting research avenue to be explored in the near future.

DATA AVAILABILITY STATEMENT

Data used in the analysis is available upon request.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

FUNDING

This research was funded by the European Union - NextGenerationEU, Mission 4, Component 2, in the framework of the GRINS -Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 –CUP D43C22003110001) and by the European Union's Horizon 2020 Research and Innovation Programme (project 'ESSPIN') under Grant Agreement No. 101061104. Camilla Lenzi acknowledges funding from the Cariplo Foundation through the project 'Digital transformation, territorial inequalities and wellbeing'.

NOTES

1 See among many others Acemoglu and Restrepo (2020) for the US, de Vries et al. (2020) and Blanas et al. (2019) for the EU, Adachi et al. (2020) for Japan, Aghion et al. (2019) for France, Dauth et al. (2021) for Germany, Caselli et al. (2021) and Dottori (2021) for Italy.

2 In this paper, we follow the definitions and the terminology introduced by Acemoglu and Restrepo (2019). Specifically, automation technologies (e.g., robot) introduce a displacement effect of automated tasks while raising the productivity of non-automated ones. The overall effect on labour demand, therefore, depends on the relative balance between the productivity and the displacement effects. Conversely, a technology creating new tasks impacts labour demand through a productivity effect (i.e., labour has a comparative advantage in the newly introduced tasks with respect to technology) and a reinstatement effect (i.e., the expansion of the task set). Together, they generate an expansion of labour demand and of the wage bill. These concepts are fully discussed in the next section.

[3] As with other types of technologies, digitalisation can also lead to displacement effects (Acemoglu, 2002). This paper, however, conceptually elaborates on the reinstatement potential of digital technologies, the least investigated aspect in existing literature (Cirillo et al., 2021). It will then empirically prove that a reinstatement effect takes place.
[4] There remains a good portion of jobs which, by contemporary technological standards, are unattractive targets for automation because of technical bottlenecks and economic feasibility as much as because human interaction and involvement are essential parts of the service to be provided (Frey & Osborne, 2017; Brynjolfsson & McAfee, 2014; Autor, 2022).
[5] The exact timing and the key technologies at the base of each industrial revolution is a matter of debate among economic and technology historians. This paper follows the partitioning proposed by Perez (2010).
[6] The opposite sign of these effects can partly explain the large heterogeneity of outcomes detected in the empirical analyses (Dauth et al., 2021).
[7] Section 5 discusses the main results in comparison with those obtained by the literature using patent data.
[8] An alternative approach to measure digitalisation is related to the exposure of occupations to new digital technologies (see for instance Fossen & Sorgner, 2022; Frey & Osborne, 2017). By this approach, however, it is not possible to separate out occupations at risk of digital automation from those that are already digital intensive.
[9] Other available indicators are: activities carried out by the company on the Internet (website, social media), types of connection used (fixed and mobile broadband), IT tools used to manage internal activities (e.g., use of enterprise resource planning (ERP), customer relationship management (CRM) software) or relationships with production chain contacts (customers, suppliers, other companies), sales from e-commerce, use of specialist skills in ICTs, electronic invoicing.
[10] This indicator presents, of course, some limitations (e.g., it includes only a specific technology; it takes into consideration firms, somehow neglecting the other actors involved in digital transformations such as intermediary platforms). However, given the still scarce data availability at the spatial level, this indicator provides a satisfactory balance between subnational data availability, cross-industry data and timespan covered.
[11] Rilevazione sulle tecnologie dell'informazione e della comunicazione nelle imprese (ICT), research files.
[12] The industries excluded from the survey are as follows: agriculture, forestry and fishing; mining and quarrying; financial and insurance activities; veterinary activities; public administration and defence, compulsory social security; education; human health and social work activities; arts entertainment and recreation; other personal service activities; activities of households as employers, undifferentiated goods and services producing activities of households for own use; activities of extraterritorial organisations and bodies.
[13] Results are robust to alternative weighting schemes applied to combine NUTS3 sectoral specialisation and NUTS3 broadband access. A sensitivity analysis was conducted by assigning the following combinations of weights to sectoral specialisation and broadband access variables to apportion the cloud adoption one at the NUTS3 level: 0.55 and 0.45, respectively; 0.45 and 0.55, respectively; 0.6 and 0.4, respectively; 0.4 and 0.6, respectively. Results remain qualitatively unchanged and are available upon request.
[14] It is worth noting that, from an empirical perspective, the two weights (i.e., the specialisation of NUTS3 regions in the survey sectors and the share of households with broadband access) have a relatively low correlation, always below 0.5.
[15] The information collected from the population constitutes the basis on which the official estimates of the employed and unemployed are derived, as well as the information on the main aggregates of the labour supply – occupation, sector of economic activity, house worked, type and duration of contracts, training. The labour force survey is harmonised at European

level as established by EU Regulation 2019/1700 of the European Parliament and of the Council and is included among those included in the National Statistical Programme, which identifies statistical surveys of public interest.

16 www.istat.it/en/files/2013/07/la_classificazione_delle_professioni.pdf, last accessed, 19 May 2023.

17 This classification corresponds to ISTAT Nomenclature and Classification of Professional Units – CP 2021. https://www.istat.it/it/archivio/18132

18 https://ec.europa.eu/eurostat/web/metropolitan-regions/background, last visited 11 May 2022.

19 Admittedly, a panel structure dataset could have some advantages; however, in this specific case, the yearly changes of employment and wage bill shares by occupational groups are very limited (data are available upon request), thus making a cross-sectional framework preferable. Importantly, results prove to be consistent to the use of alternative time spans for the measurement of the dependent variables (i.e., 2013–2019 changes or 2014–2019 changes, as shown in columns 5 and 6 of Tables A1 to A6 in the Appendix in the online supplemental data). This approach is indeed consistent with the existing literature exploiting long-term differences of employment and wage bill shares (e.g., Autor, 2019). Moreover, it is reasonable to expect that the changes in employment and wage bill shares require several years to occur, as much as that the relationship between the adoption of digital technologies and these changes takes time to develop. Lastly, the variable capturing the metropolitan nature of NUTS3 provinces is time invariant and the digitalisation variable is available only for a few years. Balancing these considerations, the cross-sectional econometric framework looked the most appropriate in the present setting.

20 Results are robust to NUTS2-clustered standard errors. Results are available upon request.

21 By looking at the results reported in Tables A7 and A8 in the Appendix in the online supplemental data, the first stage estimates indicate a satisfactory correlation between the selected instrument and the potentially endogenous technology adoption variable. The IV diagnostics reported in Table A9 in Appendix suggest that under-identification does not seem a substantial issue and no suspect biases are identified (see the Kleinberg-Paap rk weak instrument F statistic). Even though the exclusion restriction cannot be tested due to the just-identified nature of the model, the technology adoption variable seems to be exogenous in all the specification, as indicated by the endogeneity tests. Therefore, the preferrable results to be interpreted are the ones reported in Table 4 in the main text.

22 Related data and charts are available upon request.

23 The expansion of mid-skilled occupations in non-metropolitan areas might be the outcome of the relocation of specific sectors (and occupations within sectors) in non-urban areas. The retail sector is a good example in this respect: with the advent of e-commerce, the opportunity to enlarge the size of the market online has drastically increased and reached the global level, while opening a tight competition on prices and requiring tight cost-cutting strategies. Relocation to less central areas can fulfil this goal. See for a similar discussion Camagni et al. (2023).

24 The variation of the low-skilled employment share between 2012 and 2019 in metropolitan and non-metropolitan areas is -0.024 and -0.018, respectively.

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