

## The Nexus between the Digital Service Economy and Intraregional Wage Inequalities

Roberta Capello, Camilla Lenzi & Elisa Panzera

To cite this article: Roberta Capello, Camilla Lenzi & Elisa Panzera (22 May 2024): The Nexus between the Digital Service Economy and Intraregional Wage Inequalities, Economic Geography, DOI: [10.1080/00130095.2024.2343693](https://doi.org/10.1080/00130095.2024.2343693)

To link to this article: <https://doi.org/10.1080/00130095.2024.2343693>



© 2024 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group, on behalf of Clark University.



Published online: 22 May 2024.



Submit your article to this journal [↗](#)



Article views: 452



View related articles [↗](#)



View Crossmark data [↗](#)



# The Nexus between the Digital Service Economy and Intra-regional Wage Inequalities



## Roberta Capello

Department of Architecture,  
Built Environment and  
Construction Engineering  
Politecnico di Milano  
Milan  
Italy  
roberta.capello@polimi.it

## Camilla Lenzi

Department of Architecture,  
Built Environment and  
Construction Engineering  
Politecnico di Milano  
Milan  
Italy  
camilla.lenzi@polimi.it

## Elisa Panzera

Department of Architecture,  
Built Environment and  
Construction Engineering  
Politecnico di Milano  
Milan  
Italy  
elisa.panzera@polimi.it

## Key words:

digital service economy  
servitization  
sharing economy  
product service economy  
online service economy  
regions  
wage inequalities

## abstract

The upsurge in wage inequalities is a common prediction in the literature analyzing the labor market outcomes of the diffusion of information and communication technologies and automation technologies. More controversial, instead, is the relationship between wage inequalities and digital technologies. This article addresses this issue on conceptual and empirical grounds. Specifically, the article elaborates on the distinction between digital technologies adoption and digital transformation and derives a conceptual typology of the different modes of digital service economy, that is, different types of digital transformation, each characterized by specific consequences in terms of intra-regional wage inequalities. Empirically, based on an analysis of 164 European regions in the period 2009–16, the article documents that only regions characterized by the most pervasive types of digital service economy experience a rise of intra-regional wage inequalities, a result that partly mitigates the automation anxiety frequently dominating the public and, sometimes, the scholarly debates.

© 2024 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group, on behalf of Clark University. This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives License (<http://creativecommons.org/licenses/by-nc-nd/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited, and is not altered, transformed, or built upon in any way. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

**JEL codes:**

O31

O33

R11

R23

## Acknowledgments

This research has received funding from the European Union's Horizon 2020 Research and Innovation Programme (project <sup>2</sup>“UNTANGLED”) under Grant Agreement No. 101004776.

The combination of disruptive megatrends, namely, globalization and technological change, in the last couple of decades has created rather unfavorable conditions for balanced growth and sociospatial resilience, amplifying the chief paradox of present time: the co-occurrence of powerful technology (and accelerating technological change in the view of many), with stagnating median wages, increasing income inequalities, and a diffused sentiment of discontent (Rodríguez-Pose 2018; McCann 2020; Feldman, Guy, and Iammarino 2021).

Many scholars and commentators, in fact, anticipate dramatic changes if not the risk of a generalized weakening and polarization of job conditions and wages. Regardless of the estimation methods adopted, and the actual figures predicted, several authors, in fact, raised important warnings about the social and distributive consequences of the changes and compression of jobs, and consequently wages, due to the diffusion of the new technologies in businesses and society (Brynjolfsson and McAfee 2014; Frey and Osborne 2017; Nedelkoska and Quintini 2018).

The literature offers rich and consistent evidence, both at the firm and at the spatial and national level, about the increasing automation in the manufacturing environment, known in the European context as Industry 4.0 (Lasi et al. 2014), and the impact of intelligent and advanced automation technologies on the displacement of manufacturing labor force and the increase of wage inequalities (see, e.g., Graetz and Michaels 2018; Humlum 2019 for Denmark; Szalavetz 2019 for Hungary; Acemoglu, Lelarge, and Restrepo 2020 for France; Autor et al. 2020 for the US and OECD countries; Dauth et al. 2021 for Germany).

In the case of digitalization, rich evidence comes from studies in the frame of the third industrial revolution, analyzing the impact of information and communication technologies (ICT) and computerization on employment and wage polarization (Autor, Levy, and Murnane 2003; Autor and Dorn 2013; Cirillo et al. 2021). In the last few years, evidence is expanding fast but frequently in a fragmented way, dealing with selected (quantitative) firm or platform case studies (Drahokoupil and Piasna 2017); specific

technologies, for example, artificial intelligence (Edquist, Goodridge, and Haskel 2021); green technologies (Cicerone et al. 2023); specific areas, for example, industrial districts (Burlina and Montresor 2022) or specific European countries, for example Hungary (Horváth and Szabó 2019), France (Acemoglu, Lelarge, and Restrepo 2020), Italy (Büchi, Cugno, and Castagnoli 2020); if not specific types of business transformation, for example, in the manufacturing sector, as discussed in the literature on the product service economy, servitization and Industry 4.0 (Barzotto et al. 2019; De Propris and Bailey 2020; Dauth et al. 2021). Unlike the case of automation, therefore, this high heterogeneity of approaches and empirical settings make it harder to draw clear-cut conclusions about the effects of digitalization on wage inequalities, even if the initial findings seem to point to a generalized deterioration of labor market conditions and a worsening of wage inequalities, although with nuances (Biagi and Falk 2017). Moreover, with the exception of the literature on territorial servitization (De Propris and Storai 2019; Lafuente, Vaillant, and Vendrell-Herrero 2019), the regional dimension of the effects of digitalization, and its consequent transformations, have been explored limitedly.

This article enhances this growing body of literature by proposing a specific approach for conceptualizing and empirically assessing the effects of digital transformation on wage inequalities from a regional perspective.

In particular, the article posits a distinction between the pure adoption of (certain types of) digital technologies and digital transformation. In this context, digital transformation refers to the structural reorganization of production and business operations around new possible channels for value creation. A digital transformation includes the emergence of new manufacturing structures, innovative business models, and opportunities within both manufacturing and service sectors, all stemming from the integration of new digital technologies (Ng, Ding, and Yip 2013).

Importantly, the emphasis on digital transformation, rather than solely on the adoption of digital technology, requires a conceptual and empirical analysis of the effects on wage inequalities deriving from the enlargement of various forms and modes with which final services are created and delivered using digital technologies. This transformative process, defined as the *digital service economy* (Capello, Lenzi, and Panzera 2022) blurs the boundaries between products and services. This is enabled by the dematerialization or unbundling of products (e.g., a car) from the service they may provide (e.g., a ride), with service not only complementing and/or enriching products, as proposed in the case of servitization and its literature (Baines et al. 2017; Rabetino et al. 2021), but also, and increasingly, *substituting* them, with dramatic consequences for competitive dynamics; business models; and, ultimately, wage inequalities.

In this perspective, the digital service economy refers to the use of digital technologies for business purposes that enable companies to operate on online markets as primary loci for market transactions, the key distinctive trait and novelty of modern digitalization compared with the past ICT and computerization revolution (Capello, Lenzi, and Panzera 2022). The capacity of companies operating in different sectors of the economy to shift toward digital (online) markets facilitates the formation and establishment of new business models, entailing different sources of value creation and distribution. Consequently, the digital service economy may affect not only the ways of doing business and the traditional market logics (i.e., business models) but also the required

occupational profiles, as much as the reinstatement and/or displacement of specific occupations, and the subsequent wage distribution and inequalities.

Like all technological transformations, the digital service economy is a sector-driven phenomenon (Perez 2010). Economic sectors, in fact, differ in terms of profitability gains from technology adoption and, thus, in terms of propensity and/or vulnerability to a specific technological transformation (Malerba 2002). Consequently, the penetration of the digital service economy in space is (as expected) heterogeneous, as typical of any technological transformation and innovation (Capello and Lenzi 2021), since it depends on regional sectoral heterogeneity and intensity of technology adoption. Accordingly, the digital service economy can take different forms and vary across regions according to the economic sectors involved and the intensity of penetration of digital technologies, possibly leading to differentiated effects on wage inequalities (Capello, Lenzi, and Panzera 2022).

This article aims at exploring whether and how the digital service economy, and the different forms it may take place across space, can be associated with a rise of intraregional wage inequalities. On conceptual grounds, the article enriches existing literature by elaborating on the relationships between different types (and combinations) of the digital service economy and wage inequalities. This is empirically tested based on an innovative data set covering 164 EU regions in the period 2009–16.

The remainder of the article is organized as follows. After discussing the different types of digital service economy, the article elaborates on their potential impacts on wage inequalities. The section that follows presents the logic applied to identify the different types of digital service economy in European regions. This is followed by a section that presents the econometric approach used to assess their relationship with wage inequalities. The results are discussed in the penultimate section, and conclusive remarks are proposed in the final section.

## Wage Inequalities and Digital Transformation: Conceptual Framework and Expectations

### Wage Inequalities in Europe

The rise of wage inequalities in the past thirty years is well documented in the literature, showing that a small percentage of individuals and communities did enjoy improved economic prosperity while the vast majority did not benefit from the rise of aggregate wealth (Feldman, Guy, and Iammarino 2021). This increasing imbalance has been extensively detailed in the case of the US, where diverging trends started in the past century (Piketty and Saez 2003; Piketty 2014) and have continued in more recent years (Alvaredo et al. 2018; Chancel et al. 2022; Kemeny, Petralia, and Storper 2022).

A novel spatial dimension is characterizing modern inequalities in the new millennium, in sharp contrast with the reduction in inequalities (i.e., convergence), at least at the national level, in the post-WWII period (Kemeny, Petralia, and Storper 2022). This spatial divergence, at least in the US case, is largely led by the divide between an elite group of big, wealthy, resilient, and high-income superstar city-regions and the remaining ones, leading to a club convergence within the elite and the follower groups,

respectively. Similar trends apply to the UK case where the unbalanced concentration of high-skilled workers amplifies wage differences and regional labor markets disparities (Overman and Xu 2022) as much as all over OECD countries in the years following the pandemic (OECD 2022).

The EU context is exposed to these trends as well. Even if the EU may not rank top in terms of inequalities (and their rise) from a global perspective (Chancel et al. 2022), a closer look at its geography reveals sharp heterogeneity and warns against the risks of a widening of (intra and inter)regional economic divergence (Iammarino, Rodríguez-Pose, and Storper 2019). In details, Figures 1 to 3 display the geographic distribution of the median (Figure 1), the ninetieth percentile (Figure 2), and their difference (Figure 3) of the labor cost per employee within each NUTS2 region covered by the CompNet data set in 2016.<sup>1</sup> The difference between the ninetieth percentile and the median of the labor cost per employee offers information on the gap between the highest paid and the median paid occupations within each region. Even if this indicator cannot be directly interpreted as a measure of job polarization, it is still able to account for wage dispersion and thus inequalities. When the indicator increases, in fact, it is the result either of an increase of the ninetieth percentile or of a decrease of the median value of the distribution. In both cases, the differences between the highest wages and the median ones widen, thus highlighting a worsening of intraregional wage inequalities.

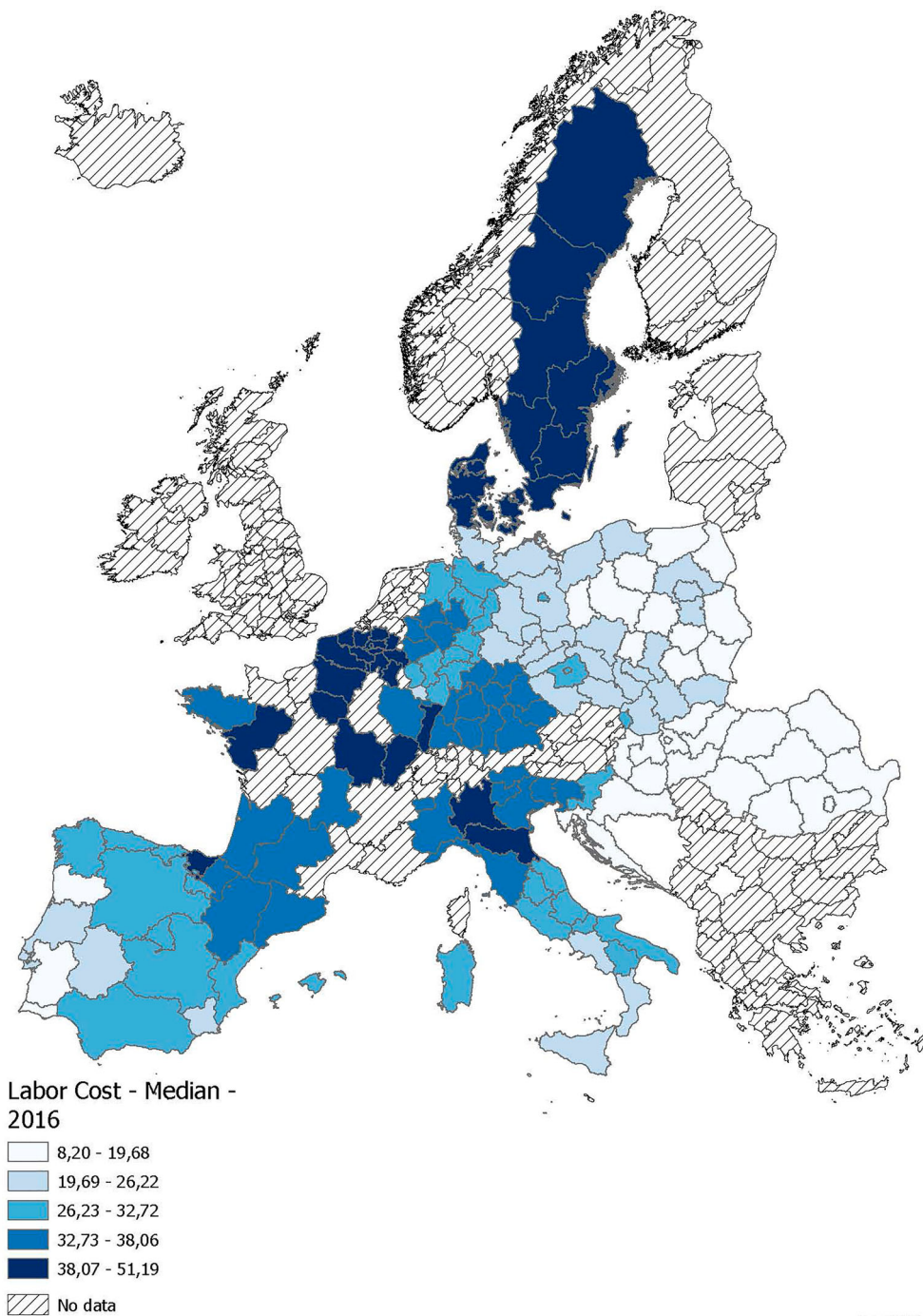
By looking at the three figures together, it clearly appears that the level of intraregional inequality can be similar, irrespective of the absolute level of wages in the region and irrespective of the level of interregional wage inequality. In fact, high-wage countries, like the Scandinavian ones, show similar intraregional inequality levels as low-wage ones, like Romania. Interestingly, and expectedly, inequalities are especially high in metropolitan areas (Kemeney and Storper 2022).

The role of automation and past waves of computerization and ICT diffusion for the observed level of wage inequalities, and their increase, is well established in the literature (Autor, Levy, and Murnane 2003; Autor and Dorn 2013; Cirillo et al. 2021). As noted above, more doubtful are the effects of modern digital technologies adoption and the ensuing digital transformation of businesses and society (Biagi and Falk 2017).

Understanding the link between the digital transformation and wage inequalities requires unpacking the multiple ways through which the adoption of digital technologies can make companies shift toward online, and primarily platform-mediated markets, as

<sup>1</sup> The Compnet (The Competitiveness Research Network) database was originally founded by the European System of Central Banks in 2012, to provide a microfounded data set covering productivity indicators for twenty European countries, including a series of labor market-related indicators available at the NUTS2 level and harmonized to allow cross-country comparability. A major advantage of CompNet's data set lies in the provision of detailed information for each indicator, including its distribution, an aspect that is particularly relevant to obtain a measure of wage inequalities. Ideally, it would have been preferable to consider the gap between the bottom (e.g., tenth percentile) and the top (e.g., ninetieth percentile) of the distribution, as is common in the literature discussing the role of technology on job polarization, meant as the exacerbated gap between well-paid skilled jobs and low-paid, least-skilled ones. Unfortunately, data unavailability prevented us from following this direction. In particular, tenth percentile data is missing for Denmark, Germany, Portugal, and Hungary. In an attempt to mitigate this issue, the indicator used is the difference between the ninetieth percentile and the median value of the distribution, which suffer less than the mean value from the presence of particularly high or low values in the wage distribution. Moreover, the difference between the top and the median wages was used rather than their ratio so as to be able to take the levels of the variable into account.

6



Esri, USGS

Figure 1. Median labor cost, 2016.

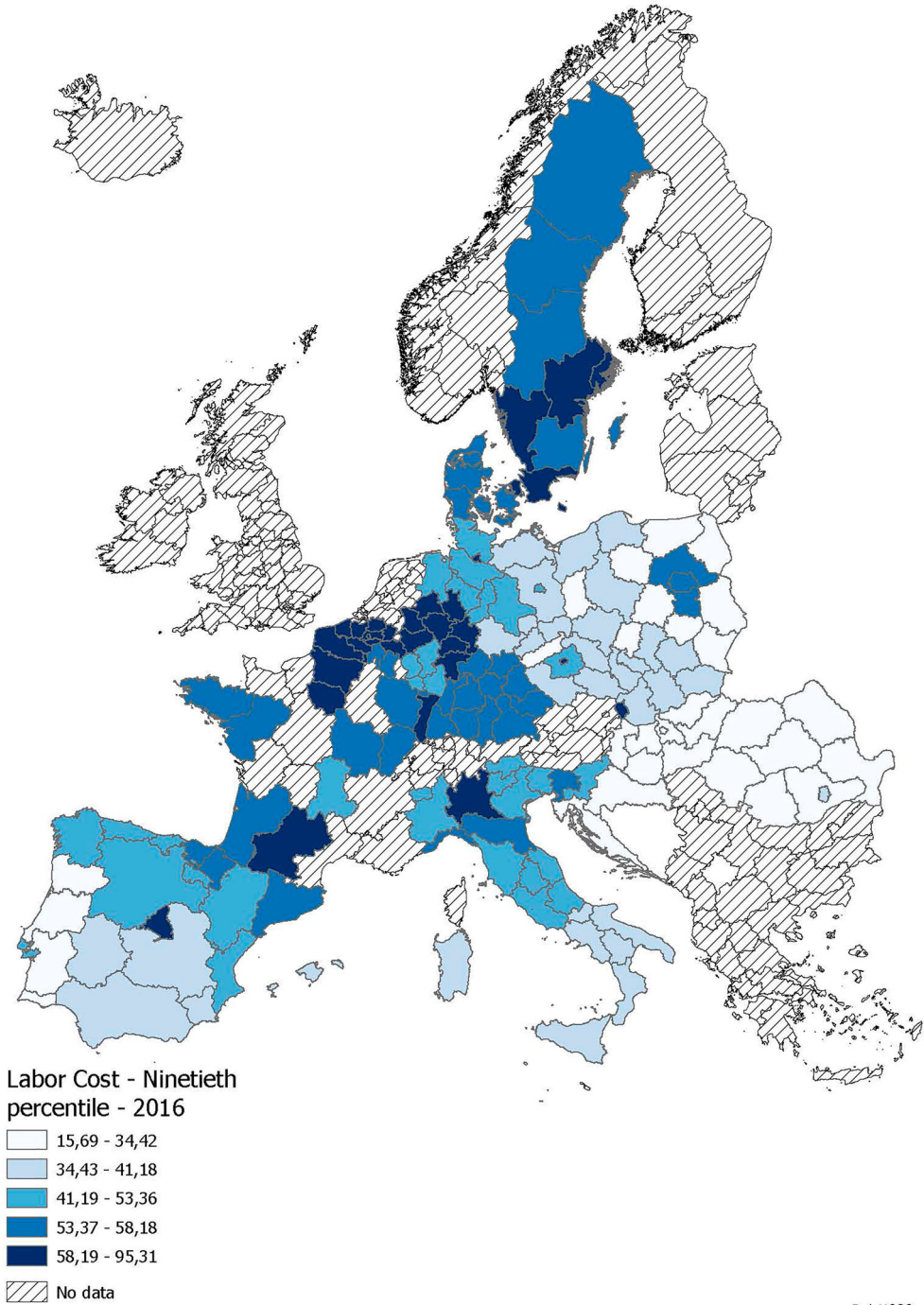
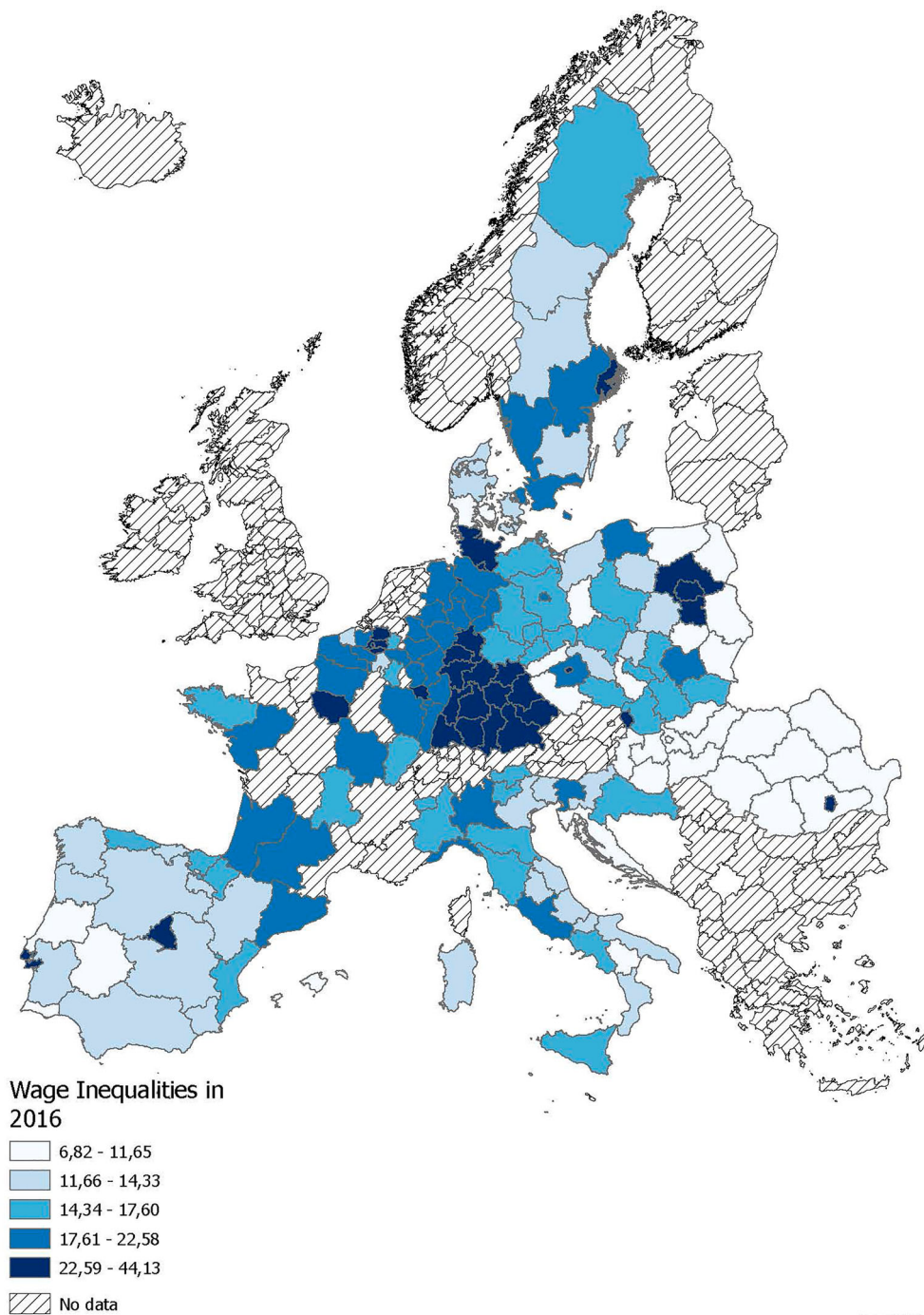


Figure 2. Ninetieth percentile labor cost, 2016.



8



Esri, USGS

Figure 3. Intraregional wage inequalities, 2016.

primary loci for economic transactions, the key distinctive trait and novelty of modern digital transformation compared with the past ICT and computerization revolution. This transformative process has been labeled in previous works as *digital service economy*, which means an economy encompassing a sprawling range of businesses, mostly based on digital platforms that sell services, products, or contents on online markets (Capello, Lenzi, and Panzera 2022).

The next section discusses possible alternative archetypes of the digital service economy and their possible link with wage inequalities.

### Digital Service Economy Archetypes and Wage Inequalities

The use of digital technologies for business purposes that enable companies to operate on online markets as primary loci for market transactions is not a univocal, homogeneous process across industries and space. Besides, the capacity of companies operating in different sectors of the economy to shift toward digital (online) markets is facilitated and/or enabled by the presence of digital platforms that influence and sometimes revolutionize the sources of value creation and distribution affecting not only the traditional market logics but also occupations and wage inequalities.

A way to typify the different forms of digital service economy is through the identification of the different players involved and digital platforms' pervasiveness in (and thus value created through and accrued from) online market transactions (Capello, Lenzi, and Panzera 2022).<sup>2</sup> Digital platforms, in fact, replace bilateral with trilateral relationships, involving a provider (of job, content, service), a user, and the platform, playing the role of *matchmaker* between providers who offer a product/service/content and users interested in using, buying, or enjoying it (Kornberger, Pflueger, and Mouritsen 2017; Koutsimpogiorgos et al. 2020). This matchmaking role can vary according to the platforms' pervasiveness in (and thus value created through and accrued from) market transactions. In their simplest form, platforms can purely serve as a technical basis to generate digital value chains involving suppliers and customers (Kornberger, Pflueger, and Mouritsen 2017). However, they can also facilitate transactions by easing the matching of buyers' and sellers' needs. In more complex forms, platforms sell their own services and products in competition with those offered by the providers hosted on the platform itself. Importantly, providers of the service, goods, or contents offered can be manufacturing firms, as well as an owner of a resource with idle capacity, or single individuals offering their spare time and job services (Koutsimpogiorgos et al. 2020).

Depending on the platforms' pervasiveness in online market transactions, it is possible to anticipate the likely distribution of value created online among platforms, providers, and users, and its implications for wage inequalities.

<sup>2</sup> The literature offers rich examples of classifications of platforms. For example, Kenney and Zysman (2016) distinguish platforms on the service offered (e.g., platforms for platforms, platforms mediating work, retail platforms, etc.); Schor (2016) proposes a distinction depending on the function played by the platform (e.g., platforms enabling durable goods to be exploited more efficiently, platforms to share assets, etc.). Each classification serves different conceptual and empirical purposes. In the present case, the classification proposed and applied shall serve the goal of identifying the actors involved in digital market transactions and the value share each party accrues from online market transactions.

A first type of digital service economy can be associated with the concept of *product-service* or *servitization economy* introduced in the late 1980s (Vandermerwe and Rada 1988).<sup>3</sup> Servitization is a strategy put in place by manufacturing firms to offer services together with products, mixed offerings like advanced product-service systems if not physical products, as services; for example, customers subscribe to a long-term contract and pay for use, performance, or availability of this resource (see for reviews and Baines et al. 2017; Rabetino et al. 2021 on servitization; Baines et al. 2007 on product-service systems). Digitalization is boosting and enriching this traditional idea of servitization, although the transition to digital servitization is not automatic or simple (Gebauer et al. 2021). In this respect, digital platforms can facilitate this transition by improving relationships with customers (front-end platforms) as well as with suppliers (back-end platforms), and manufacturers may rely on outsourced platforms as well as developing their own to provide platforms as a service (Kohtamäki et al. 2019).

10 The competences requested by (digital) servitization strategies can be acquired and/or developed within the servitized manufacturing firm or sourced from local service providers, as shown in the rich literature on territorial servitization and local product-service innovation systems (see, e.g., Lafuente, Vaillant, and Vendrell-Herrero 2019; Sforzi and Boix 2019; De Propriis and Bailey 2020; Vendrell-Herrero and Bustinza 2020; Vaillant et al. 2021).

The need for new competences may support not only a business refocusing, but also a reorientation, if not an upgrade, of the worker profile for jobs requiring higher educational attainment and skill level, more complex cognitive and abstract tasks, and, thus, higher wages (Dauth et al. 2021). This shift may also rely on draining talents from competing local service firms or from pushing local business partners to upgrade their offers (De Propriis and Storai 2019).

However, the magnitude of the overall effects on labor markets can be hampered by the extent of servitization processes within existing manufacturing firms. Estimates for European countries indicate that the share of servitized manufacturing firms vary in a range from 3 percent to 10 percent (Vendrell-Herrero and Bustinza 2020).

The restricted diffusion may significantly limit the impact of this type of digital service economy on intraregional wage inequalities, with impacts mainly affecting single firms or their local service providers. *Overall, the impact of this form of digital service economy on intraregional wage inequalities is expected to be modest and mostly dependent on an increase of top wages associated with the upgraded jobs and task.*

A second type of digital service economy can be associated with the *sharing economy* phenomenon, generally referring to the creation of new online markets for underutilized assets or idle resources (e.g., a spare seat in a car, a spare bedroom, spare time), made temporarily accessible to other users upon payment, based on a peer-to-peer exchange. The owner of the resource can exchange its excess capacity, which in an offline situation would have had no value (Frenken and Schor 2017). The sharing economy generally involves trilateral transactions, characterized by the exchange of products, services, or contents through digital intermediaries (Schor 2016).

<sup>3</sup> The two terms are used interchangeably in the article, with awareness of the debate on their differences (Baines et al. 2017; Rabetino et al. 2021).

In this case, two main effects can be expected. First, high-skill, elite jobs can be created by the intermediary platforms. In most cases, platform owners are superstar firms, with fast increasing profits despite a limited number of employees (i.e., the so-called business model of mass without scale). Superstar firms may create high-skill, elite jobs (e.g., managers or executives as well as engineers) for their headquarters and research facilities. This effect, however, is very limited in number, and highly concentrated in those few (mostly non-European) regions hosting such activities. Such a small number is insufficient to substantially affect the overall regional employment level and, consequently, wage inequalities. On the other hand, a displacement effect can take place, hitting on low-skill workers. In fact, the provision of customer-to-customer services can enhance competition with traditional offline businesses (e.g., BlaBlaCar versus traditional transport services), and can erode their market share in favor of online businesses and, especially, digital platforms (Rahman and Thelen 2019). The contraction of business opportunities can lead to a displacement of workers employed in those activities and, indirectly, to a reduction of their wage conditions (Frenken and Schor 2017). The gravity of such a contraction is unclear given the uncertainty of the overall weight on the economy of the substitution between offline and online businesses. *The overall impact of the sharing economy on intraregional wage inequalities, then, is expected to be driven by the negative effects generated on traditional offline businesses and their employees, worsening intraregional wage inequalities.*

Finally, the last and most complex (as well as diffused) form of digital service economy refers to situations in which digital platforms provide services, products, and contents (e.g., mobility solutions, food and beverage services, payment systems) without owning the assets necessary to produce and/or deliver such services or goods and has been labeled as an *online service economy*. The online service economy shares with the servitization economy the importance of the dematerialization of assets or products and the unbundling of products from the service a product can offer (De Propris and Storai 2019). Uber, for instance, unbundles the product (a car) from the service it may provide (a ride), that is, the product is dematerialized into a service (a ride). Unlike the servitization economy, however, digital platforms in the online service economy do not own the assets necessary to provide goods, services, or contents but do own the data on providers and users so as to match demand and supply instantaneously with low transaction and search costs (Kornberger, Pflueger, and Mouritsen 2017). In fact, Uber does not possess a fleet of cars, just as Foodora or Justeat operate without having restaurant facilities.

Importantly and differently from the previous cases, in the online service economy, platforms enable new business and job opportunities, thus deeply affecting labor markets in terms of employment level and wage inequalities. The online service economy, in fact, relies frequently on on-call contingent workers, using their own tools and equipment to perform the productive work associated with the supplied service, giving rise to huge problems in terms of low pay, quality, and stability of new jobs created. These workers are commonly known in the literature and in the press as gig workers (Stanford 2017).

Therefore, three main effects can be expected as a consequence of the diffusion of the online service economy. As in the sharing economy, there can be an increase in high-

**Table 1**

*Digital Service Economy: Effects on Business Activities, Local Labor Markets and Expectations on Intra-regional Wage Inequalities*

	Effects on Business Activities	Impact on Local Labor Markets	Expectations on Intra-regional Wage Inequalities
<i>Product service (servitization) economy</i>	New activities like customised design, repair and maintenance, consultancy	Jobs requiring higher educational attainment and skill level, with a reorientation of the tasks content of jobs away from intensive routine manual tasks	Modest effect, mostly dependent on an increase of top wages
<i>Sharing economy</i>	Creation of new online markets for underutilized assets or idle resources	Creation of high-skill, elite jobs by intermediary platforms Displacement of low-skill workers due to crowding out effects on traditional offline businesses	Worsening of intra-regional wage inequalities
12 <i>Online service economy</i>	Creation of new online markets for dematerialized products without asset ownership	Creation of high-skill, elite jobs by intermediary platforms Displacement of low-skill workers due to crowding out effects on traditional offline businesses New job opportunities, especially for on-call contingent workers	Worsening of intra-regional wage inequalities

skill, cognitive, elite jobs and their wages, mostly linked with intermediary platforms, and more marked shadow effects on traditional offline workers at risk of being displaced or at least suffering a downward pressure on wages. More importantly, a third effect might arise related to the expansion of local low-skill, low-paid, and insecure jobs. These effects are probably greater in the areas where online services are consumed and thus especially in urban areas where the online service economy can develop faster because of the high concentration of demand. Taken together, these effects lead us to expect *a worsening of intra-regional wage inequalities in the case of the online service economy.*

Table 1 summarizes the logic and the expectations about the effects of each archetype of digital service economy on intra-regional wage differentials, tested in the empirical part of the article.

## Measuring Inequalities and the Identification of the Digital Service Economy in European Regions

The empirical test of the hypotheses set out in the previous section rests on two crucial measurement issues.

The first relates to the best indicator available for capturing wage gaps in European NUTS2 regions. As discussed in “Wage Inequalities in Europe,” important data constraints prevent us from capturing wage gaps by comparing top wages (i.e., the ninetieth percentile) against bottom ones (i.e., the tenth percentile). The solution adopted was to

use the difference between the ninetieth percentile and the median wage in each region, an acceptable indicator of wage gaps.<sup>4</sup>

The second issue relates to the identification of the different types of digital service economy (and their possible spatial combinations) in European regions, which follows the approach developed by Capello, Lenzi, and Panzera (2022). In this perspective, the geographic distribution of the digital service economy depends on the location of the different actors involved in each type of digital service economy. By their own nature, it is substantially impossible to identify the specific location of digital platforms. Providers and users linked to platforms, instead, can be easier to map as well as their transition to online markets measured through their intensity of digital transformation enabled by the adoption of digital technologies.

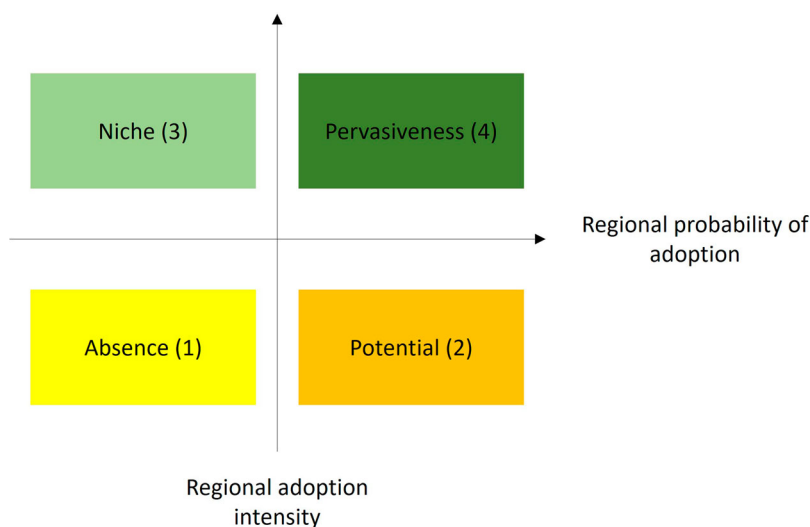
Empirically, therefore, the different types of digital service economy can be distinguished, based on the specialization and intensity of use of digital technologies in specific and representative sectors, namely, manufacturing in the case of product service or servitization economy, food and beverage service activities, and retail in the case of the online service economy. In these sectors, companies are not expected to operate fully online. However, the transition to online markets is most likely mediated by the operation of platforms, thus altering offline and online activities competition, at the detriment of offline ones, typically characterized by a very local dimension.

Importantly, the specialization of a region in each of these sectors, on its own, does not guarantee the presence of a digital transformation, which also requires a high intensity of adoption of digital technologies. Conceptually, therefore, the combination of the regional sectoral specialization with the regional sectoral adoption intensity can give rise to four possible situations (Figure 4):

- absence of digital service economy, when both regional sectoral adoption intensity and sectoral specialization are below the national mean;
- potential digital service economy, when regional sectoral adoption intensity is below the national mean in sectors of specialization;
- niche digital service economy, when adoption intensity is high in sectors that are not those of specialization;
- pervasive digital service economy, when both indicators are above the national average.

As regards the sharing economy, regional adoption is measured through the share of the population exchanging goods and services online. The diffusion of digital technologies in the local population instead accounts for the probability of the phenomenon and is measured with the regional share of the population using the internet daily. Crossing the two indicators, the same four situations highlighted above (and presented in Figure 4) arise.

<sup>4</sup> The use of CompNet microdata, unfortunately did not represent an improvement in this empirical EU-wide setting. Microdata, in fact, are available for a limited number of countries. See <https://www.comp-net.org/eu-technical-support-instrument-tsi/data/>.



14

Figure 4. Development stages of the digital service economy.

The data used for the computation of these indicators—standardized with respect to the national values to mitigate strong country effects<sup>5</sup>—has been sourced from EUROSTAT. Specifically, regional sectoral specialization in the different sectors is analyzed on the basis of EUROSTAT Structural Business Statistics. For digital technology sectoral adoption, the indicator used is the regional intensity of online sales (i.e., the regional share of firms with at least 1 percent of turnover from online sales), sourced from EUROSTAT at the sectoral national level, next apportioned at the regional level.<sup>6</sup>

The most appropriate indicator for digital technologies adoption is a matter of debate (Biagi and Falk 2017; Capello, Lenzi, and Perucca 2022). In particular, the use of online sales as an indicator of digitalization has a particularly attractive feature in this context with respect to the use of data on computerization, ICT, or patents in artificial intelligence. In fact, it allows capturing the extent to which specific economic sectors can make the transition toward online markets, mostly managed by intermediary platforms, that is, the intensity of the digital transformation and not simply the intensity of digital technology adoption.

The reference year for the variables (i.e., probability and intensity of adoption) used to compute the four classification variables indicating the status of development of each specific type of digital service economy is 2010.

Importantly, the different types of digital service economy may coexist in regional economies and combine heterogeneously across space. European regions, therefore, have been grouped according to their predominant type of digital service economy obtained through a *k*-means cluster analysis, using as inputs the categorical variables representing the four development stages (Figure 4) for each of the three types of digital

<sup>5</sup> This choice leads to excluding from the analysis those countries composed of a single NUTS2 region (i.e., Malta, Luxembourg, Cyprus, Estonia, Latvia).

<sup>6</sup> More specifically, the regional online sales have been obtained by apportioning the national value according to two weights: the share of population with internet access and the regional sectoral weight (see Capello and Lenzi [2021] for details).

service economy. By this analysis, five digital service economy patterns have been identified:

1. *Underdeveloped digital service economy*: regions in this cluster are characterized by the lack of any type of digital service economy and are generally weak regions from the technological and economic point of view.
2. *Sharing economy*: regions in this cluster exhibit a pervasive sharing economy. Other types of digital service economy are instead less developed and remain either potential or absent.
3. *Product-service (servitization) economy*: regions in this cluster predominantly show a strong industrial profile and are characterized by an either pervasive or potential servitization economy. A remarkable trait of this cluster is the absence of all the other types of digital service economy.
4. *Online service economy*: regions in this cluster show a pervasiveness of the online service economy.
5. *Fully developed digital service economy*: regions in this cluster score high in terms of all types of digital service economy and are characterized by a favorable environment to technology adoption and use in business and society. These regions have a metropolitan nature confirming that urbanization economies help the digital service economy develop faster because of the high concentration of demand.<sup>7</sup>

## The Econometric Framework

On econometric grounds, to estimate the impact of the different types of digital service economy and its spatial combinations on intraregional wage inequalities, we estimated the following stylized equations:

$$\begin{aligned} \text{Wage inequalities}_{r,t} = & \alpha + \beta_1 \text{digital service economy}_r + \beta_2 X_{r,t-1} \\ & + \beta_3 \text{country}_r * \text{time fixed effects}_t + v_r + \varepsilon_{r,t} \end{aligned} \quad (1)$$

$$\begin{aligned} \text{Wage inequalities}_{r,t} = & \alpha + \beta_1 \text{digital service economy patterns}_r \\ & + \beta_2 X_{r,t-1} + \beta_3 \text{country}_r * \text{time fixed effects}_t + v_r + \varepsilon_{r,t} \end{aligned} \quad (2)$$

where wage inequalities in region  $r$  and at time  $t$  are made dependent on a series of regional level determinants  $X_{r,t-1}$ , with both an idiosyncratic and a time-varying random error term ( $v_r + \varepsilon_{r,t}$ ). The period considered is 2009–16, and the regions considered are 164 NUTS2 regions.<sup>8</sup>

The key explanatory variable in [equation \(1\)](#) is the type of *digital service economy*, which aims to account for the impact of each type of digital service economy on

<sup>7</sup> We would like to thank an anonymous reviewer for underlining this interpretation.

<sup>8</sup> Probably, wage inequalities, as much as other variables capturing labor market structure, vary slowly over time. However, in the balance between sample size, time invariant nature of the focal variables, and greater precision of panel estimates, a static panel setting seemed preferable to a dynamic panel one or a cross-section one. This approach, importantly, allows highlighting the association between the penetration of the digital service economy and observed levels of inequalities.



intraregional wage inequalities. To emphasize the consequences on intraregional wage inequalities of the full pervasiveness stage of types of digital service economy, four dummy variables have been introduced, taking value 1, if it has a pervasive status, and 0 otherwise.<sup>9</sup>

The key explanatory variable in equation (2) instead is *digital service economy patterns*, which aims to capture the effect of the spatial combination of different types of digital service economy as identified through the cluster analysis (Capello, Lenzi, and Panzera 2022). A set of five dummy variables has been introduced, with each dummy accounting for one of the five digital service economy patterns characterizing each European region, that is, *underdeveloped digital service economy*, *sharing economy*, *product service economy*, *online service economy*, *fully developed digital service economy*, *underdeveloped digital service economy* being the reference case.

Besides country by year fixed effects, a set of control variables,  $X_{r,t-1}$ , measured at the NUTS2 level is included in both equations (1) and (2) in line with existing literature in the field (e.g., Acemoglu and Restrepo 2020), namely,<sup>10</sup>

16

- the median age of the population, in order to control for the different opportunities of finding a job at older ages and wage dispersion across population cohorts (Dauth et al. 2021);
- the female share and the foreign share of active population, as both categories of workers might be characterized by lower average wages (Autor and Dorn 2013);
- the tertiary educated population, as higher education workers generally enjoy higher wages (Acemoglu and Autor 2011);
- the risk of job automation, as labor markets characterized by a high percentage of replaceable workers generally might show lower average wages (Nedelkoska and Quintini 2018);
- the share of metropolitan population to control for the predominant urban location of the digital service economy, the higher wages (and inequalities) in cities (Florida 2017), as well as their greater market potential (Krugman 1991);
- the change of the share of people employed in low- and high-skills occupations to control for the structure of occupations and wages in the labor market and possible mechanical correlations (Autor et al. 2022);

<sup>9</sup> The four dummy variables originate from four different categorical variables (corresponding to the development stages of each type of digital service economy). More in detail, the four categorical variables range from one to four, accounting, respectively, for *absence*, *potential*, *niche*, or *pervasiveness* (see Figure 4) of each type of digital service economy. A dummy variable has been created for each type of digital service economy taking the value of 1, when pervasive, and 0 otherwise. Results, available upon request, are qualitatively unchanged when the dummy variables are introduced separately.

<sup>10</sup> The list of variables does not include the unemployment rate, typically considered in the wage curve literature (Blanchflower and Oswald 1990) but not in the one on wage inequalities and technological change (e.g., Acemoglu and Autor, 2011). An important difference in the present setting, with respect to the wage curve literature, refers to the dependent variable used: wage dispersion in the present case against wage level in the wage curve case. While, admittedly, unemployment can be related to wage levels, in general, the exclusion of the unemployment variable could alter the results on wage dispersion should it alter top and median wages in different proportions. Evidence seems to exclude this effect when considering the gap between top (ninetieth percentile) and median (fiftieth percentile) wages (Iacono and Ranaldi 2020).

**Table 2***Description and Sources of the Variables*

Variable	Description	Data Source
Wage inequalities	Regional difference between the ninetieth percentile and the median of the average wage (labor cost/number of employees)	CompNet
Type of digital service economy	Set of four dummy variables each flagging regions with a pervasive type of digital service economy	Authors' elaboration based on Eurostat data
Digital service economy patterns	Categorical variable taking value: <ol style="list-style-type: none"> <li>1. for underdeveloped digital service economy regions</li> <li>2. for sharing economy regions</li> <li>3. for product service (servitization) economy regions</li> <li>4. for online service economy regions</li> <li>5. for fully developed digital service economy regions</li> </ol>	Authors' elaboration based on Eurostat data
Median age	Median age of the regional population	Eurostat
Foreign active population	Share of foreign active population on total active population	Eurostat
Female active population	Share of female active population on total active population	Eurostat
Tertiary educated population	Percentage of population (> fifteen years) with tertiary education	Eurostat
Share of population in metropolitan areas	Percentage of total population living in urban areas of each NUTS2	Eurostat
Share of employment at high risk of automation	Share of jobs at high risk of automation	Authors' elaboration*
Low-skilled employment share variation	Five-year average variation of the share of people employed in low skills occupations (ISCO 9 code occupations)	Eurostat
High-skilled employment share variation	Five-year average variation of the share of people employed in high skills occupations (ISCO 1 and 2 code occupations)	Eurostat
Employment share in manufacturing (C)	Employment share in manufacturing	Eurostat
Employment share in food and beverage service activities (I56)	Employment share in food and beverage service activities	Eurostat
Employment share in wholesale and retail trade (G)	Employment share in wholesale and retail trade	Eurostat

\* For details on the construction of this variable, see Capello and Lenzi (2021).

- the employment share in the sectors, representative of each type of digital service economy, to take into account the role of sectoral differences on intraregional wage inequalities (Dauth et al. 2021).

In the attempt to mitigate endogeneity issues, which might affect some of the control variables (e.g., female employment share or the tertiary educated employment share), all the explanatory variables have been one year lagged with respect to the dependent variable. This strategy, though still a standard approach in the literature, has some limitations and might not completely exclude endogeneity concerns related to some of the control variables (Reed 2015); yet, it may remain sufficient in the present context where the focus is on the association between the unfolding of the digital service economy with the observed level of wage inequalities.

Variables description and sources are displayed in Table 2, while the correlation matrix and VIF (variance inflation factor) are available in the Appendix (Tables A1 and A2) and do not show alarming cases of multicollinearity (O'Brien 2007).

18 The econometric analysis was performed in a panel setting consisting of eight years. Random effects rather than fixed effects were adopted because of the presence of time-invariant explanatory variables (i.e., the dummy variables for each type of digital service economy, the categorical variable for the digital service economy patterns, country dummies, risk of job automation). The Hausman test has been performed to confirm the appropriateness of the random versus fixed effects.<sup>11</sup> The estimates reported below, then, are based on linear robustified generalized least squares (GLS) random effects.

## Results and Discussion

The results obtained by estimating equations (1) and (2) are displayed in Table 3, suggesting interesting messages.

First, whatever the specific type of digital service economy, except for the product service (servitization) economy, its diffusion at a large scale raises concerns in terms of increasing inequalities. As reported in Table 3, column 1, a high penetration of the *sharing economy* model is positively associated with intraregional wage inequalities, as shown by its positive and statistically significant coefficient. It can be argued that when the *sharing economy* is widespread and diffused, its consequences on wage distribution can be detrimental and increase intraregional wage inequalities. The substitution of traditional activities by new ways of exchanging goods and services and

---

<sup>11</sup> Furthermore, in consideration of the possible spatial interdependencies across regional units, we followed the general-to-simple model selection rule and the test procedure proposed by Elhorst (2010) to decide whether and which spatial model is the most appropriate in the present empirical context. We started by estimating a spatial Durbin model (SDM) by using a row-standardized spatial weight matrix whose elements, the  $w_{ij}$  spatial weights, represent the row-standardized inverse distance between the centroids of the  $i$  and  $j$  regions. The average distance between any  $i$  and  $j$  NUTS2 regions in the sample is 166 kilometers; the distance matrix, accordingly, has been truncated at 250 kilometers. Wald tests allow rejecting the significance of the spatially lagged dependent and independent variables. Wald tests implemented upon the estimation of spatial autoregressive model (SAR), spatial lag of Xs model (SLX) and spatial error model (SEM) converge in excluding a serious concern of spatial dependence in this empirical setting. Results of spatial dependence tests are available upon request.

Table 3

*The Digital Service Economy and Wage Inequalities*

Dependent Variable: Wage Inequalities	1	2
Median age	-0.382*** (0.137)	-0.372*** (0.137)
Foreign active population	-2.297 (6.543)	-2.126 (6.563)
Female active population	-0.812 (5.588)	-0.236 (5.564)
Tertiary educated population	15.425*** (3.573)	15.704*** (3.645)
Share of metropolitan population	4.246*** (1.031)	4.858*** (1.135)
High-skill employment share variation	-0.245 (1.879)	-0.275 (1.884)
Low-skill employment share variation	3.816 (2.323)	3.753 (2.336)
Employment share at high risk of automation	-12.656 (9.893)	-18.383* (10.097)
Employment share in manufacturing (C)	2.882 (4.629)	1.948 (4.440)
Employment share in food and beverage activities (I56)	-35.113 (21.633)	-30.196 (21.126)
Employment share in wholesale and retail trade (G)	5.767 (3.590)	6.388* (3.636)
Sharing economy	3.187*** (0.732)	
Product service (servitization) economy	0.028 (0.679)	
Online service economy (sector I56)	1.013 (1.105)	
Online service economy (sector G)	1.605* (0.902)	
Sharing economy		2.576*** (1.042)
Product service (servitization) economy		0.364 (1.059)
Online service economy		0.562 (1.152)
Fully developed digital service economy		3.526*** (1.144)
Constant	31.840*** (6.072)	31.283*** (6.096)
R <sup>2</sup>	0.75	0.72
Hausman test – Chi2 (p-value)	21.92 (1.00)	41.17 (1.00)

N = 164 × 8 = 1,312. Country by year fixed effects included. Robust standard errors in parentheses. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

by new online agents therefore generates displacement effects when it is pervasive in a region.

Differently, a significant penetration of the *product service (servitization) economy* does not seem to contribute to expanding wage inequalities. Even though a strong specialization in the manufacturing sector might be related to both lower average wages, as

well as with a request for more specialized and qualified professionals performing elite jobs, overall, its effect does not significantly influence intraregional wage inequalities. As hypothesized at the beginning, the limited diffusion of product service (servitization) economy within manufacturing may significantly reduce the impact of the product service economy on wage inequalities, with effects mainly touching on single firms or their local service providers.

Similarly, but unexpectedly, the pervasiveness of the *online service economy* related to food and beverage service activities is not associated with higher wage inequalities. Probably, this type of digital service economy mainly allows for a more efficient way of delivering products and services without dramatically changing the labor demand structure. Another potential explanation may be related with the typologies of labor contracts stipulated in this sector, which could be temporary, nonstandard, or self-employment kind (and therefore not captured by the indicator used in this analysis). Measurement issues concerning the new gig jobs being created can also be an explanation for the unexpected result. The informal nature of such jobs makes them difficult to  
20 be captured by official labor statistics.

Interestingly, the pervasiveness of the *online service economy* linked with the retail sector shows a significant association with wage inequalities. In this case, the adoption of digital technologies enables new and wider markets to be reached, possibly requiring expert and highly paid professionals. At the same time, greater competition and risks arise when the sector opens to broader markets beyond local ones. A decrease of the median wages might happen in order to face these altered threat conditions.

These messages are overall confirmed in Model 2, which displays the results obtained through the estimation of [equation \(2\)](#), and highlights the association between the different *digital service economy patterns* and wage inequalities. In fact, even if the consequences of each specific type of digital service economy are interesting *per se*, the reality suggests that they do combine in space. Therefore, their respective impacts and consequences on labor market inequalities might be strengthened but also mitigated.

Expectedly, the output of this second set of estimates shows that the association between the digital service economy and intraregional wage inequalities is strong and statistically significant in the case of the fully developed digital service economy.

Interestingly, the sharing economy pattern also shows a significant association with intraregional wage inequalities. Substitution effects linked with this pattern and shadow effects generated on traditional offline businesses and their employees seem to prevail, leading to the erosion of traditional offline actors' market share and an increase of wage inequalities.

In the other cases, even if each of the single type of digital service is highly pervasive in the local economy, its relation with intraregional wage inequalities is overall nil.

Control variables suggest that wage inequalities tend to be particularly high in metropolitan settings, which are generally characterized by a younger and more educated population. This result confirms the spatial concentration of inequalities within cities, partly because of the gap in income per capita between metropolitan versus

nonmetropolitan settings. Importantly, this result raises warnings about the modes through which the economic advantages of cities are actually enjoyed by the urban population (Lenzi and Perucca 2023).

Differently, the variable capturing the risk of automation presents (somewhat unexpectedly) a negative sign, significant in Model 2. There might be alternative explanations for this finding. First, a high risk of automation mainly characterizes low-skill and low-paid occupations. If these latter occupations represent a relevant share of the local labor market, the median and top wages are likely to fall, and the gap between them will fall accordingly. Beside this statistical effect, there might be additional effects in place. In fact, the risk of job automation and labor displacement might be compensated by (unobserved) reinstatement effects, that is, the creation of new and higher-quality jobs, thus mitigating the rise of wage inequalities, a particularly likely effect in the case of the product-service economy (Dauth et al. 2021). Moreover, automation might still be potential and not actually realized, meaning that job displacement might have not yet taken place, and good manufacturing jobs might be still available. Finally, even in the case of actual automation and consequent job displacement, the displaced jobs might be as low paid as the new service ones to which the displaced workers switch, with no final effects on wage inequalities.<sup>12</sup> As a last remark, it is quite interesting to observe the positive association between the share of employment in retail and wage inequalities, consistent with the expectations put forward in “Wage Inequalities and Digital Transformation: Conceptual Framework and Expectations” and the literature (Stanford 2017).

These findings, therefore, align only up to a certain extent with warnings raised in the literature, as well as in the press, which tend to attribute to automation and digitalization most of the causes for the increase in wage inequalities, leading to what has been identified as the *automation anxiety* (Autor 2015). Results from Table 3, in fact, help in partially mitigating such an anxiety, suggesting that the observed rise of wage inequalities can be associated only with some of the transformations in place, namely, the sharing economy and the combination of all types of digital service economy.

Altogether, these results highlight important messages and policy implications, discussed in the concluding section.

## Conclusions

The upsurge in wage inequalities largely predicted in the literature and feared in the media debate has partly found confirmation in the analysis conducted in this article. Our conclusions, however, enable also nuancing if not mitigating some of the most severe and pessimistic forecasts about the consequences of the diffusion of the new technologies on the labor market.

---

<sup>12</sup> We would like to thank an anonymous reviewer for pushing us to reflect further on this result and the limits of the risk of the automation variable.

Although the rapid diffusion of advanced digital technologies in services and the consequent emergence of different types of digital service economy can conceptually widen intraregional wage inequalities, specific conditions shall be in place to detect such rising inequalities.

The empirical results highlight that the pervasiveness of each type of digital service economy is not sufficient to affect intraregional wage inequalities, except for the sharing economy. It is rather the spatial combination of all types of digital service economy that matters in affecting such inequalities, adding, or even multiplying, the effects of single transformations.

In fact, when a single type of digital service economy prevails as the unique one in a region, its impact on intraregional wage inequalities is limited. In the case of the product-service (servitization) economy, for instance, the limited impacts are probably the outcome of a reduced weight of this type of business model on local economies. Even if some impacts on wages can be conceptually envisaged, particularly affecting and improving the ones of high-skill, elite workers, these effects do not sizably alter the structure of occupations and wages in local labor markets. When, instead, the types of different digital service economy coexist, their effects on wage inequalities can be added together.

Taken together, these results suggest that popular fears about the possible consequences of the diffusion of the new technologies are not fully misplaced, and wage inequalities do rise over time. However, regions are not similarly exposed to these risks, and only some of them are actually experiencing a deterioration of their wage inequality conditions. This conclusion has some relevance in terms of policy warnings. In fact, for the most exposed regions, the rise in their wage inequalities can represent an urgent and immediate issue requiring a timely policy response and intervention. Differently, in other regions not yet similarly exposed to these risks, anticipatory policy interventions could be appropriate to avoid a widening of intraregional wage disparities in the future, once the digital service economy becomes dominant. In both groups of regions, however, tackling wage inequalities is likely to be a priority in the policy agenda in the near future.

The digitalization transformation, therefore, shall require a broad range of actions (and not just on the labor markets), so as to limit its consequences in terms of inequalities. These actions are especially necessary in urban areas, where multidimensional inequalities are in place, possibly multiplying those related to digital transformation (Capello and Lenzi 2023; Lenzi and Perucca 2023). The definition of the set of policy instruments is however (and as usual) a hard task, “more easily written than done effectively” (Johnson 1997, 53) and will probably require a mix of interventions ranging across fields as diverse as minimum wage regulations (Autor, Mindell, and Reynolds 2022), an enhanced and capillary diffusion of advanced digital infrastructure, and a continuous investment in skills modernization and upgrading. The centrality of most of these themes to the strategic goals of national resilience and recovery plans in the time frame of the NextGenerationEU represents a unique opportunity, not to be missed, to tackle the growing inequalities in

the EU, and to prevent their consequences for the mounting (political) resentment of the resident population (Rodríguez-Pose 2018; Iammarino, Rodríguez-Pose, and Storper 2019; McCann 2020).

## References

- Acemoglu, D., and Autor, D. 2011. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, volume 4, part B, ed. D. Card and O. Ashenfelter, 1043–171. San Diego, CA: North Holland Elsevier.
- Acemoglu, D., Lelarge, C., and Restrepo, P. 2020. Competing with robots: Firm-level evidence from France. Working Paper 26738. Cambridge, MA: National Bureau of Economic Research. <https://www.nber.org/papers/w26738>.
- Acemoglu, D., and Restrepo, P. 2020. Robots and jobs: Evidence from US labor markets. *Journal of Political Economy* 128 (6): 2188–244. doi:10.1086/705716.
- Alvaredo, F., Chancel, L., Piketty, T., Saez, E., and Zucman, G., eds. 2018. *World inequality report 2018*. Paris: World Inequality Lab.
- Autor, D. H.. 2015. Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspective* 29 (3): 3–30. doi:10.1257/jep.29.3.3.
- Autor, D., Chin, C., Salomons, A. M., and Seegmiller, B. 2022. New frontiers: The origins and content of new work, 1940–2018. Working Paper 30389. Cambridge, MA: National Bureau of Economic Research.
- Autor, D. H., and Dorn, D. 2013. The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review* 103 (5): 1553–97. doi:10.1257/aer.103.5.1553.
- Autor, D. H., Dorn, D., Katz, L. F., Patterson, C., and Van Reen, J. 2020. The fall of the labor share and the rise of superstar firms. *Quarterly Journal of Economics* 135 (2): 645–709. doi:10.1093/qje/qjaa004.
- Autor, D. H., Levy, F., and Murnane, R. J. 2003. The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics* 118 (4): 1279–333. doi:10.1162/003355303322552801.
- Autor, D., Mindell, D., and Reynolds, E. 2022. *The work of the future: Building better jobs in an age of intelligent machines*. Cambridge: MIT Press.
- Baines, T., Bigdeli, A. Z., Bustinza, O. F., Guang, V., Baldwin, J., and Ridgway, K. 2017. Servitization: Revisiting the state-of-the-art and research priorities. *International Journal of Operations & Production Management* 37 (2): 256–78. doi:10.1108/IJOPM-06-2015-0312.
- Baines, T. S., Lightfoot, H. W., Evans, S., Neely, A., Greenough, R., Peppard, J., and Alcock, J. R. 2007. State-of-the-art in product-service systems. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 221 (10): 1543–55. doi:10.1243/09544054JEM858.
- Barzotto, M., Corradini, C., Fai, F., Labory, S., and Tomlinson, P. R., eds. 2019. *Revitalising lagging regions: Smart specialisation and industry 4.0*. Oxford: Routledge.
- Biagi, F., and Falk, M. 2017. The impact of ICT and e-commerce on employment in Europe. *Journal of Policy Modeling* 39 (1): 1–18. doi:10.1016/j.jpolmod.2016.12.004.
- Blanchflower, D. G., and Oswald, A. J. 1990. The wage curve. *Scandinavian Journal of Economics* 92 (2): 215–35. doi:10.2307/3440026.
- Brynjolfsson, E., and McAfee, A. 2014. *The second machine age: Work, progress and prosperity in a time of brilliant technologies*. London: W. W. Norton.



- Büchi, G., Cugno, M., and Castagnoli, R. 2020. Smart factory performance and Industry 4.0. *Technological Forecasting and Social Change* 150 (January): 119790. doi:10.1016/j.techfore.2019.119790.
- Burlina, C., and Montresor, S. 2022. On the territorial embeddedness of the fourth industrial revolution: A literature review about how industry 4.0 meets industrial districts. *Scienze Regionali, Fascicolo 1/2022*: 63–82. doi:10.14650/102498.
- Capello, R., and Lenzi, C. 2021. *The regional economics of technological transformations—Industry 4.0 and servitisation in European regions*. London: Routledge.
- . 2023. Automation and labour market inequalities: A comparison between cities and non-cities. *npj Urban Sustainability* 3, art. 56. doi:10.1038/s42949-023-00135-8.
- Capello, R., Lenzi, C., and Panzera, E. 2022. The rise of the digital service economy in European regions. *Industry and Innovation* 30 (6): 637–63. doi:10.1080/13662716.2022.2082924.
- Capello, R., Lenzi, C., and Perucca, G. 2022. The modern Solow paradox. In search for explanations. *Structural Change and Economic Dynamics* 63 (December): 166–80. doi:10.1016/j.strueco.2022.09.013.
- 24 Cicerone, G., Faggian, A., Montresor, S., and Rentocchini, F. 2023. Regional artificial intelligence and the geography of environmental technologies: Does local AI knowledge help regional green-tech specialization? *Regional Studies* 57 (2): 330–43. doi:10.1080/00343404.2022.2092610.
- Cirillo, V., Evangelista, R., Guarascio, D., and Sostero, M. 2021. Digitalization, routineness and employment: An exploration on Italian task-based data. *Research Policy* 50 (7): art. 104079. doi:10.1016/j.respol.2020.104079.
- Chancel, L., Piketty, T., Saez, E., and Zucman, G., eds. 2022. *World inequality report 2022*. Paris: World Inequality Lab.
- Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. 2021. The adjustment of labour markets to robots. *Journal of the European Economic Association* 19 (6): 3104–53. doi:10.1093/jeaa/jvab012.
- De Propris, L., and Bailey, D., eds. 2020. *Industry 4.0 and regional transformations*. London: Routledge.
- De Propris, L., and Storai, D. 2019. Servitizing industrial regions. *Regional Studies* 53 (3): 388–97. doi:10.1080/00343404.2018.1538553.
- Drahokoupil, J., and Piasna, A. 2017. Work in the platform economy: Beyond lower transaction costs. *Intereconomics—Review of European Economic Policy* 52 (6): 335–40. <https://www.intereconomics.eu/contents/year/2017/number/6/article/work-in-the-platform-economy-beyond-lower-transaction-costs.html>. doi:10.1007/s10272-017-0700-9.
- Edquist, H., Goodridge, P., and Haskel, J. 2021. The internet of things and economic growth in a panel of countries. *Economics of Innovation and New Technology* 30 (3): 262–83. doi:10.1080/10438599.2019.1695941.
- Elhorst, P. 2010. Applied spatial econometrics: Raising the bar. *Spatial Economic Analysis* 5 (1): 1742–72. doi:10.1080/17421770903541772.
- Feldman, M., Guy, F., and Iammarino, S. 2021. Regional income disparities, monopoly and finance. *Cambridge Journal of Regions, Economy and Society* 14 (1): 25–49. doi:10.1093/cjres/rsaa024.
- Florida, R. L. 2017. *The new urban crisis: How our cities are increasing inequality, deepening segregation, and failing the middle class—And what we can do about it*. London: Basic Books, Hachette.
- Frenken, K., and Schor, J. 2017. Putting the sharing economy into perspective. *Environmental Innovation and Societal Transitions* 23 (June): 3–10. doi:10.1016/j.eist.2017.01.003.
- Frey, C. B., and Osborne, M. A. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change* 114:254–80. doi:10.1016/j.techfore.2016.08.019.
- Gebauer, H., Paiola, M., Saccani, N., and Rapaccini, M. 2021. Digital servitization: Crossing the perspectives of digitization and servitization. *Industrial Marketing Management* 93 (February): 382–88. doi:10.1016/j.indmarman.2020.05.011.

- Graetz, G., and Michaels, G. 2018. Robots at work. *Review of Economics and Statistics* 100 (5): 753–68. doi:10.1162/rest\_a\_00754.
- Horváth, D., and Szabó, R. Z. 2019. Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technological Forecasting and Social Change* 146 (September): 119–32. doi:10.1016/j.techfore.2019.05.021.
- Humlum, A. 2019. Robot adoption and labor market dynamics. Working Paper. Madrid: Center for Monetary and Financial Studies. <https://www.cemfi.es/ftp/pdf/papers/Seminar/humlumJMP.pdf>.
- Iacono, R., and Ranaldi, M. 2020. The wage curve across the wealth distribution. *Economics Letters* 196 (November): art. 109580. doi:10.1016/j.econlet.2020.109580.
- Iammarino, S., Rodríguez-Pose, A., and Storper, M. 2019. Regional inequality in Europe: Evidence, theory and policy implications. *Journal of Economic Geography* 19 (2): 273–29. doi:10.1093/jeg/lby021.
- Johnson, G. E. 1997. Changes in earnings inequality: The role of demand shifts. *Journal of Economic Perspectives* 11 (2): 41–54. doi:10.1257/jep.11.2.41.
- Kemeny, T., Petralia, S., and Storper, M. 2022. Disruptive innovation and spatial inequality. *Regional Studies*. doi:10.1080/00343404.2022.207682.
- Kenney, M., and Zysman, J. 2016. The rise of the platform economy. *Issues in Science and Technology* 32 (3). <https://issues.org/rise-platform-economy-big-data-work/>.
- Kohtamäki, M., Parida, V., Oghazi, P., Gebauer, H., and Baines, T. 2019. Digital servitization business models in ecosystems: A theory of the firm. *Journal of Business Research*, 104 (November): 380–92. doi:10.1016/j.jbusres.2019.06.027.
- Kornberger, M., Pflueger, D., and Mouritsen J. 2017. Evaluative infrastructures: Accounting for platform organization. *Accounting, Organization and Society* 60 (July): 79–95. doi:10.1016/j.aos.2017.05.002.
- Koutsimpogiorgos, N., van Slageren, J., Herrmann, A. M., and Frenken, K. 2020. Conceptualizing the gig economy and its regulatory problems. *Policy & Internet* 12 (4): 525–45. doi:10.1002/poi3.237.
- Krugman, P. 1991. Increasing returns and economic geography. *Journal of Political Economy*, 99 (3): 483–99. doi:10.1086/261763.
- Lafuente, E., Vaillant, Y., and Vendrell-Herrero, F. 2019. Territorial servitization and the manufacturing renaissance in knowledge-based economies. *Regional Studies* 53(3): 313–19. doi:10.1080/00343404.2018.1542670.
- Lasi, H., Fettke, P., Kemper, H-G., Feld, T., and Hoffmann, M. 2014. Application-pull and technology-push as driving forces for the fourth industrial revolution. *Business & Information Systems Engineering* 6:239–42. doi:10.1007/s12599-014-0334-4.
- Lenzi, C., and Perucca, G. 2023. Economic inequalities and discontent in European cities. *npj Urban Sustainability* 3 (26). doi:10.1038/s42949-023-00104-1.
- Malerba, F. 2002. Sectoral systems of innovation and production. *Research Policy* 31(2): 247–64. doi:10.1016/S0048-7333(01)00139-1.
- McCann P. 2020. Perceptions of regional inequality and the geography of discontent: Insights from the UK. *Regional Studies* 54 (2): 256–67. doi:10.1080/00343404.2019.1619928.
- Nedelkoska, L., and Quintini, G. 2018. Automation, skills use and training. OECD Social, Employment and Migration Working Papers. Paris: OECD. [https://www.oecd-ilibrary.org/employment/automation-skills-use-and-training\\_2e2f4eea-en](https://www.oecd-ilibrary.org/employment/automation-skills-use-and-training_2e2f4eea-en).
- Ng, I. C. L., Ding, D. X., and Yip, N. 2013. Outcome-based contracts as new business model: The role of partnership and value-driven relational assets. *Industrial Marketing Management* 42 (5): 730–43. doi:10.1016/j.indmarman.2013.05.009.
- O'Brien, R. M. 2007. A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity* 41:673–90. doi:10.1007/s11135-006-9018-6.
- OECD. 2022. *OECD regions and cities at a glance 2022*. Paris: OECD Publishing. [https://www.oecd-ilibrary.org/urban-rural-and-regional-development/oecd-regions-and-cities-at-a-glance-2022\\_14108660-en](https://www.oecd-ilibrary.org/urban-rural-and-regional-development/oecd-regions-and-cities-at-a-glance-2022_14108660-en).

- Overman, H. G., and Xu, X. 2022. Spatial disparities across labour markets. *IFS Deaton Review of Inequalities*. <https://ifs.org.uk/inequality/spatial-disparities-across-labour-markets/>.
- Perez, C. 2010. Technological revolutions and techno-economic paradigms. *Cambridge Journal of Economics* 34 (1): 185–202. doi:10.1093/cje/bep051.
- Piketty, T. 2014. *Capital in the twenty-first century*. Cambridge, MA: Belknap Press of Harvard University Press.
- Piketty, T., and Saez, E. 2003. Income inequality in the United States, 1913–1998. *Quarterly Journal of Economics* 118 (1): 1–41. doi:10.1162/00335530360535135.
- Rabetino, R., Kohtamäki, M., Brax, S. A., and Sihvonen, J. 2021. The tribes in the field of servitization: Discovering latent streams across 30 years of research. *Industrial Marketing Management* 95 (May): 70–84. doi:10.1016/j.indmarman.2021.04.005.
- Rahman, K. S., and Thelen, K. 2019. The rise of the platform business model and the transformation of twenty-first-century capitalism. *Politics & Society* 42 (2): 177–204. doi:10.1177/0032329219838932.
- Reed, W. R. 2015. On the practice of lagging variables to avoid simultaneity. *Oxford Bulletin of Economics and Statistics* 7 (5): 897–905. doi:10.1111/obes.12088.
- Rodríguez-Pose, A. 2018. The revenge of the places that don't matter (and what to do about it). *Cambridge Journal of Regions Economy and Society* 11 (1): 189–209. doi:10.1093/cjres/rsx024.
- 26 Schor, J. 2016. Debating the sharing economy. *Journal of Self-Governance and Management Economics* 4 (3): 7–22.
- Sforzi, F., and Boix, R. 2019. Territorial servitization in Marshallian industrial districts: The industrial districts as a place-based form of servitization. *Regional Studies* 53 (3): 398–409. doi:10.1080/00343404.2018.1524134.
- Stanford, J. 2017. The resurgence of gig work: Historical and theoretical perspectives. *Economic and Labour Relations Review* 28 (3): 382–401. doi:10.1177/1035304617724303.
- Szalavetz, A. 2019. Industry 4.0 and capability development in manufacturing subsidiaries. *Technological Forecasting & Social Change* 145 (August): 384–95. doi:10.1016/j.techfore.2018.06.027.
- Vaillant, Y., Lafuente, E., Horváth, K., Vendrell-Herrero, F. 2021. Regions on course for the fourth Industrial Revolution: The role of a strong indigenous T-KIBS sector. *Regional Studies* 55 (10–11): 1816–28. doi:10.1080/00343404.2021.1899157.
- Vandermerwe, S., and Randa, J. 1988. Servitization of business: Adding value by adding services. *European Management Journal* 6(4): 314–24. doi:10.1016/0263-2373(88)90033-3.
- Vendrell-Herrero, F., and Bustinza, O. F. 2020. Servitization in Europe. In *Industry 4.0 and regional transformations*, ed. L. De Propris and D. Bailey, 24–41. London: Routledge.

## Appendix

**Table A I**

### Correlation Matrix

#	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Median age															
2	Foreign active population	0.14														
3	Female active population	0.12	0.05													
4	Tertiary educated population		0.34	0.56												
5	Share of metropolitan population	-0.08	0.30	0.29	0.49											
6	High-skill employment share variation	-0.13	-0.09	0.25	0.19	0.14										
7	Low-skill employment share variation			-0.07	-0.19		-0.30									
8	Share of employment at high risk of automation	-0.21	-0.27	-0.10	-0.31	-0.14										
9	Employment share in manufacturing (C)	0.36	0.58		0.15	0.13	-0.14		-0.13							
10	Employment share in food and beverage service activities (I56)	0.06	-0.26		-0.31	-0.20		0.11	0.08	-0.33						
11	Employment share in wholesale and retail trade (G)	-0.06	0.24	0.09	0.17	0.30			-0.14	0.38	-0.08					
12	Sharing economy		0.11	0.14		0.16			-0.19	0.07	-0.15	0.18				
13	Product service (servitisation) economy	-0.06				0.07				-0.13	0.4	-0.09				
14	Online service economy (sector I56)		0.19	0.25	0.33	0.42	0.07		-0.14	0.17	-0.25	0.20	0.14	-0.16		
15	Online service economy (sector G)	-0.09	0.23	0.12	0.13	0.31			-0.08	0.10	-0.09	0.46	0.22		0.28	
16	Digital service economy patterns	-0.24	0.18	0.13	0.11	0.27	0.12			-0.06	0.06		0.16	0.45	0.22	0.36

Note: the table displays correlations significant with  $p < 0.05$ .

Table A2

VIF

Variables	Model 1	Model 2
Median age	5.17	5.42
Foreign active population	3.79	3.84
Female active population	3.96	3.95
Tertiary educated population	5.34	5.07
Share of metropolitan population	2.22	2.15
High-skill employment share variation	1.61	1.62
Low-skill employment share variation	1.45	1.45
Share of employment at high risk of automation	5.39	5.39
Employment share in manufacturing (C)	5.65	5.52
Employment share in food and beverage service activities (I56)	2.74	2.08
Employment share in wholesale and retail trade (G)	2.31	1.80
Sharing economy	1.62	
28 Product service (servitization) economy	1.62	
Online service economy (sector I56)	1.84	
Online service economy (sector G)	1.69	
Sharing economy pattern		2.87
Product service (servitisation) pattern		2.45
Online service economy pattern		2.68
Fully developed digital service economy pattern		3.45
Mean VIF	3.20	3.23