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# The diffusion of digital skills across EU regions: structural drivers and polarization dynamics

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## Abstract<sup>1</sup>

The digital transformation is an important driver of long-run productivity growth and, as such, it has the potential to promote a more inclusive and sustainable growth. However, digital capabilities, crucial to develop and govern new digital technologies, are unevenly distributed across European regions increasing the risk of divergence and polarization. By taking advantage of a set of original indicators capturing the level of digital skills in the regional workforce, this work analyzes the factors shaping the process of digital skill accumulation in the EU over the period 2011-2018. Relying on transition probability matrices and dynamic random effects probit models, we provide evidence of a strong and persistent regional polarization in the adoption and deployment of digital skills. Further, we investigate whether European Funds (European Regional Development Fund, Cohesion Funds, and European Social Funds) are capable to shape the digitalization process and to favor regional convergence.

**JEL codes:** O14; O30; O38

**Key words:** Digital transition, Skills, Labour markets, Persistence, Regional development, EU policies

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## 1. Introduction

Digitalization is at the top of the European Commission (EC)’s policy agenda. It is considered the key to promote firms’ national and international competitiveness, efficiency of key public services (e.g., communication, transports), convergence between and within member states. The importance of digitalization is also reflected in the EC’s main policy actions: about 20% of the Next Generation EU budget (150 billions) is allocated to digitalization-related missions (EC, 2020) while even more resources are devoted to specific plans such as the ‘Digital Compass’<sup>2</sup> and the ‘European Chips Act’<sup>3</sup>. Indeed, strengthening Europe’s digital capabilities has become an undeferrable goal given the growing conflicts between the two major digital powerhouses, i.e. the US and China. In this context, narrowing the gap *vis-à-vis* digital leaders and increasing European (digital) autonomy becomes a matter of utmost strategic urgency: to strengthen Europe’s ‘digital endowments’ (i.e. infrastructure, technologies and skills) becomes essential to reduce the risk of technological backwardness (and related risks of import dependency) with its associated negative implications in terms of competitiveness and growth (Crespi et al. 2021).

Digitalization cannot occur without the widespread diffusion of digital skills (DS). The latter are crucial on both the supply and the demand-side as well as to ensure the spreading of digital technologies at a broader societal-level. As regards the supply-side, the absorptive capacity of companies, industries and regions is strongly related to the quantity and quality of skills the former are endowed with (see for instance D’Este et al., 2014 and Fusillo et al. 2022). This is particularly true in the case of digital technologies given the strong innovation-skill complementarity and the importance of tacit knowledge and idiosyncratic skills for the development of IT-related innovations. DS are also a key component of National, Local and Regional Innovation Systems (NIS, LIS and RIS)<sup>4</sup> playing a relevant role in the processes of regional diversification and structural change (on this point, see, among others, Castellacci et al. 2020 and Santoalha et al. 2021, Balland et al., 2021). Where DS are abundant and up-to-date, public bodies (and, more generally, organizations of territorial significance) are more likely to increase their efficiency by introducing IT innovations and to support the diffusion of knowledge and innovation opportunities. As for the demand side, the diffusion of DS is essential to ensure a sustained demand for digital products and services. In fact, the mere availability of digital goods and services does not ensure demand-side absorption. Consumption of digital goods and services often requires the availability of skills (more or less advanced depending on the degree of sophistication of the digital goods/services at stake) without which demand may not materialize. From a structural point of view, the growth of digital

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<sup>2</sup> For a detailed description of the Digital Compass, see: <https://futurium.ec.europa.eu/en/digital-compass>

<sup>3</sup> The European Chips Act is illustrated here: <https://digital-strategy.ec.europa.eu/en/policies/european-chips-act>

<sup>4</sup> A review of the literature on LIS and RIS has been recently provided by Fernandes et al. (2021) and for an empirical test see Cirillo et al. (2019).

industries in both manufacturing and services can only go hand in hand with the consolidation of a strong (digital) knowledge-base.

Indeed, the digitalization of EU economies and the associated diffusion of DS follow a highly heterogeneous pattern. This reflects the process of structural core-periphery polarization that a number of contributions have already documented (see, among others, Celi et al. 2018, 2020, 2021; Grabner and Hafele, 2020). These studies show how digital capabilities tend to concentrate in Central and Northern European member states, while less intense digitalization is detected in Southern and Eastern ones. A significant heterogeneity is also observable at the regional level. Internal divides concern all relevant economic and innovation variables and, of course, digitalization is no exception (Reveiu et al. 2022). European regions that are characterized by relatively low levels of economic activity, investments and institutional quality tend also to show poor digitalization endowments, including DS. That is, in a context characterized by persistent structural polarization and economic divides, digitalization assumes the form of an additional fault line between (i.e. core-periphery divide) and within (i.e. regional divide) European economies. If this is the context, it is not surprising that EU policies aimed at addressing structural gaps between member states and regions also abound. Such policies are designed to support the structural upgrading of weaker countries and regions in order to favor their convergence towards best-performer levels. Even in this case, however, the EC's efforts do not prove sufficient to halt the ongoing polarization process (Grabner et al. 2020). On the other hand, it is worth noticing that a relevant effort to promote convergence can also be found in the NGEU: almost all national plans allocate a larger amount of resources to those structurally fragile regions that have been most severely hit by the Covid-19 crisis.

Against this background, this work analyses the digitalization of the European economy focusing on a rather neglected yet crucial element: the diffusion of DS across EU regions. We investigate the determinants of the diffusion of DS paying attention to structural processes (i.e. convergence/divergence between regions) and accounting explicitly for the role of European regional, cohesion and labor market-related funds (European Cohesion Fund-ECF, European Social Fund-ESF, European Regional Development Fund-ERDF). Following closely the approach proposed by Castellacci et al. (2020), DS are distinguished according to their level of complexity: *user*, *practitioner* and *developer*. In this way, we not only account for the share of DS characterizing each EU region; but also for the degree of sophistication of these skills, a key element to be taken into account in order to properly assess the actual structural quality of the (digital) knowledge base that is observable at the regional level. In fact, while the skills needed to 'simply' use digital technologies are now widespread and easily transferable; those needed to adapt or even design and modify digital technologies are rarer and require greater investments. Being able to distinguish the degree of complexity of DS allows us to explore structural heterogeneities (and their potential evolution over time) characterizing the digitization process in a more precise and in-depth way.

Our key findings and related contributions to the extant literature can be summarized as follows. First, the distribution of DS across EU regions is characterized by a strong heterogeneity reflecting the core-periphery polarization already documented by the previous literature (Celi et al. 2018; Perez-Morote et al. 2020). Second, polarization does not seem to attenuate over time, although some changes in specific areas are observable. Third, polarization increases with the degree of complexity of the DS: practitioner and, even more so, developer skills are way more concentrated in core regions (e.g., high income regions in Central and Northern Europe) as compared to peripheral ones. Fourth, DS upgrading (i.e. regions increasing their relative share of DS) turns out to be driven by some key structural determinants: share of tertiary educated workers, share of workers employed in high-tech and knowledge-intensive industries, share of workers employed in large firms. Concerning the role of EU policies, our baseline model (using a broad DS measure including all dimensions: user, practitioner and developer) shows that the ECF is the only fund having a positive relationship with EU regions' DS endowment. The ESF, in turn, does not seem to be significantly associated with regions' DS upgrading: only a poor association with 'user skills' (the less complex component of our DS indicator) is detected. Remarkably enough, the ERDF displays a negative relationship with the same type of DS.

The article is organized as follows. Section 2 briefly reviews the literature on the diffusion of DS in Europe, with a specific focus on regional studies; while Section 3 spells out the research questions. Section 4 illustrates the data used for the analysis and reports a detailed mapping of the regional (and dynamic) distribution of DS relying on Transition Probability Matrices (TPM) to provide a first glance of the structural dynamics - i.e. upgrading, downgrading and persistence - taking place in Europe. Section 5 illustrates the econometric strategy and reports the results while Section 6 concludes discussing the main policy implications.

## **2. The diffusion of digital skills in Europe: a review of the literature**

In recent years, the attention of European policy makers on the diffusion of DS has kept on growing. The former EC's Vice President Neelie Kroes has recently argued: 'the online world is becoming a bigger part of everything we do. No wonder these [digital] skills are becoming central in the job market'. Such a growing attention is also testified by the number of dedicated policy actions as well as by the flourishing of EC's technical reports focusing on DS (see, for example, Gareis et al. 2014). In the latest Digital Economy and Society Index Report (European Commission, 2022), there is an entire section dedicated to the state of DS in Europe. The DESI Report puts it boldly: 'All Europeans need digital skills to study, work, communicate, access online public services and find trustworthy information...The European Commission has set targets in the European skills agenda and the digital education action plan to ensure

that 70% of adults have basic digital skills by 2025. These initiatives aim to reduce the level of 13-14 years-old who underperform in computing and digital literacy from 30% (2019) to 15% in 2030.<sup>5</sup> A number of other initiatives - including the *European Digital Skills and Jobs Platform*, an initiative launched under the Connecting Europe Facility Programme aimed at providing information and resources on DS, as well as training and funding opportunities - can be detected, all confirming how much this issue is relevant to European policy makers. The same cannot be said of the scientific and, in particular, of the empirical literature. In fact, there are few contributions analyzing the diffusion of DS in Europe and even fewer analyses providing a comprehensive regional mapping including in-depth evidence on drivers and barriers to skill upgrading (some notable exceptions are: Camagni and Capello, 2005; Castellacci et al. 2020; Santoalha et al. 2021). One of the fundamental reasons for such a lack of empirical research is the poor availability of data and indicators allowing to properly measure the diffusion of DS.

The literature focusing on DS can be divided into two main streams. The first stream adopts a rather broad perspective focusing on the so-called ‘digital divide’<sup>5</sup> - i.e. the gap between high and low DS which can divide citizens, students, workers, rural and urban areas, regions and economies -, investigating its causes and discussing the effectiveness of policies aimed at reducing it (among others, see Van Dijk, 2008; Zillien and Marr, 2013; Helsper and Van Deursen, 2015; Hidalgo et al. 2020). These contributions devote a lot of attention to elements such as citizens’ ‘digital literacy’<sup>6</sup> or student performance in digitally related fields (for a comparison between the US and Europe digital performance, see Rückert et al. 2020). The key hypothesis is that the opportunities for growth, innovation and development of economies are inversely related to the relative intensity of the digital divide affecting them. A similar argument is put forth regarding regions and, more specifically, territorial development gaps (Thonipara et al. 2020).

The second stream of literature focuses on workers’ DS exploring their determinants as well as their linkages with the economic (and innovative) performance of firms, industries, regions and economies. The ‘individual returns’ of DS have been recently investigated by Falck et al. (2021) relying on the Programme for the International Assessment of Adult Competencies (PIAAC) database which provides comparable information on DS for 19 OECD countries. Building their hypotheses on the Autor et al. (2003)’s task-approach, the authors find that DS can contribute to increase the abstract task content of jobs and decrease their routine and manual task content with a final positive impact on workers’ earnings. Calvino et al. (2022) study the diffusion and impact of DS on a number of firm-level outcomes relying on a large sample of Italian companies. Their analysis shows that the low digitalisation of Italian firms, especially of SMEs, can be traced back to the low levels of three factors: i) workers’ skills, ii) management capabilities, and iii) accumulation of intangible assets. With specific reference to DS, their empirical

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<sup>5</sup> One of the first comprehensive definitions of the digital divide has been provided by the OECD (2001).

<sup>6</sup> According to Castellacci et al. (2020), digital literacy “involves not just technical knowledge but also the hybridization of traditional competences to heighten the capacity of reading, writing, researching and communicating”.

analysis shows that micro and small firms with high-skilled workers experience higher productivity returns from technology adoption. No less relevantly, where the firm-level endowment of DS is substantial the beneficial effects of infrastructural elements, such as ultra-fast broadband connection, seem to increase too. By the same token, large shares of DS turn out to have a positive impact on the effectiveness of public policies aimed at promoting companies' productivity.

Few studies, in turn, concentrate their attention on the regional diffusion of DS, as we do here. Relying on a conceptualization of DS that is very close to ours, Castellacci et al. (2020) identify DS as a key driver of regional diversification processes, new industry emergence and structural upgrading. Adding to the literature on regions' 'smart specialization' (Foray, 2013; Boschma and Giannelle, 2014), Castellacci and colleagues argue that DS are key to enable access to external advanced knowledge and information as well as to allow sectors closer to the production of ICTs to upgrade existing industrial activities<sup>7</sup>. Following up on Castellacci et al. (2020)'s contribution, Santoalha et al. (2021) analyze the relationship between DS, diversification and relatedness focusing on regions that attract and develop new activities with high technological proximity to existing know-how. More specifically, they test whether and how capabilities associated with ICTs infrastructures play a role in explaining regional green diversification. Their main hypothesis is that DS, by amplifying the remit of cognitive skills has the potential to 'facilitate the knowledge codification and diffusion that is at the core of recombinant innovations' (Frenken et al., 2012; Montresor et al. 2022). Applying their model to a sample of EU regions observed during the period, Santoalha et al. (2021) show that regions displaying a relatively higher share of DS are more likely to specialise in new technological domains, especially green ones.

Capello et al. (2022) adopt a spatial approach to assess the way in which the 'digital service economy' is spreading (heterogeneously) across EU regions. They detect a strong divide between the most industrialised regions (e.g., north-eastern Spain, Rhine-Rhur Valley, Northern Italy, Silesia), where digital value creation models are more pervasive mobilizing significant amounts of investments and skills; and less developed ones (e.g., the Italian Mezzogiorno, southern regions of Portugal and Spain), where digitalization seems to spread more slowly and without the generation of relevant capabilities. Reveiu et al. (2020) look at EU regions to investigate the relationship between DS and labor market resilience during and after crises. Focusing on a 14-year long time span (2006–19), these authors show that EU regions characterized by strong digital endowments - i.e. digital capital and skills - are significantly more resilient *vis-à-vis* external shocks and crises. In addition, digital factors turn out to be significantly stronger predictors of labor market resilience as compared to generic human capital and R&D expenditure.

No contributions explicitly explore the role of DS in shaping LIS and RIS. However, Rodriguez-Pose and Crescenzi (2008) and, more recently, Fernandes et al. (2022) emphasize how the complex interaction

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<sup>7</sup> Castellacci et al. (2020, p. 2) emphasize that half of the EU's regions have indicated ICT-related areas as priorities of their smart specialization strategies.

between local and external knowledge, on the one hand, with local and external socioeconomic and institutional conditions, on the other, can shape the innovation capacity of each region (Antonelli and Colombelli, 2018). In this respect, the abundance of high-end DS - i.e. particularly the more sophisticated ones related to the adaptation and creation of new digital technologies - turn out to be crucial for regions to seize the opportunities for change and diversification that the digital paradigm offers. The uneven spatial distribution of (radical) innovation and skills is at the center of the analyses by Crescenzi et al. (2020) and Kemeny et al. (2022). Focusing on agglomeration patterns and inequalities, these authors highlight a generalized process of polarization according to which innovation opportunities are concentrated in key hubs (most often large cities hosting MNFs) benefiting from self-reinforcing mechanisms that shield their privileged position. In such a context, skills are polarized too. Key hubs and 'affluent places' hosting the major educational and research institutions which, in turn, act as a 'magnet' attracting large inflows of high-skilled students and workers.

Finally, the role of demand factors and structural peculiarities of sectors in shaping digitalization dynamics across some key European economies (Germany, France, Italy, Spain, Portugal and the Netherlands) has been recently analyzed by Reljic et al. (2021). Testing the impact of digital technologies on European employment and distinguishing between different professional categories - managers, technicians, clerks and blue collars - they found that higher digitalisation, in terms of digital capital deepening, is associated with job creation in the case of managers and with a reduction in the employment of clerks whose numbers, on the other hand, increase with greater digital intermediate inputs. Taking into account structural heterogeneities in terms of demand flows, R&D and process innovation, the authors emphasize the relevance of DS and organizational capabilities in explaining the uneven impact of digitalization across occupational groups.

This brief review has shown how the empirical literature on the diffusion of DS in Europe is scant, not providing any comprehensive evidence concerning structural and policy drivers as well as obstacles hampering the diffusion process. This work aims at filling this literature gap taking advantage of a unique integrated dataset (see Section 4 for a detailed description of the data) which allows exploring long-term patterns of DS accumulation; processes of convergence/divergence; joint action of supply, demand and structural drivers; as well as the role of EU funds (EUCF, ESF and ERDF) in shaping the digitalization of European regions. Against this background, the next section spells out the main research questions that are empirically addressed in Sections 4 and 5.

### **3. Research Questions**

The first research question (RQ1) concerns the spatial diffusion of DS. Given their tacit, local and cumulative nature, DS are likely to be heterogeneously distributed across regions. Tacit knowledge is in



fact hardly transferrable and tends to emerge in specific areas characterized by favorable supply and demand conditions (Dosi et al. 2000; Dosi and Marengo, 2015; Fanti et al. 2021). As a result, regions that first accumulate tacit knowledge, digital competences, capabilities and related innovative capacity are likely to increase that advantage at the expense of latecomers. By the same token, DS tend to be concentrated in areas characterized by strong education and research institutions, prevalence of large innovative firms and labor market institutions that favor the accumulation of new competences (Rodriguez-Pose and Crescenzi, 2008; Castellacci et al. 2020). Such a persistent heterogeneity can in turn foster divergence and polarization between technologically and economically strong areas and weaker ones<sup>8</sup>. Building on these considerations, RQ1 can be spelled out as follows:

**RQ1.** *Is there a process of structural divergence and polarization across EU regions as regards the diffusion of DS?*

The second research question (RQ2) concerns the role of key supply, demand and structural factors that may shape the regional diffusion of DS. A first set of factors relates to EU regions' structural and technological characteristics. We test whether areas characterized by large shares of high-tech and knowledge-intensive productions, a significant number of big firms or by a relatively larger amount of patents per capita, all things being equal, are also more abundant in terms of DS. The overall economic strength of EU regions, in turn, is accounted for by including value added per employee. Here, the theoretical expectation is quite straightforward: structurally stronger regions are expected to display an equally strong DS endowment (Crescenzi et al. 2020; Caravella et al. 2021). The second set of factors relates to region-specific labor market characteristics: relative shares of young, tertiary educated, permanent and non-EU workers are accounted for. In this case, regions characterized by a young, well-educated and stable labor force are expected to be in a better position to develop and accumulate DS (for an analysis of the relationship between labor market characteristics, skills and innovation development see, among others, Kleinknecht, 2020). With no clear ex-ante expectation about the relative importance of each factor, RQ2 is thus formulated as follows:

**RQ2.** *What are the structural factors contributing the most to the diffusion of DS across EU regions?*

The third research question (RQ3) focuses on the role of EU funds in promoting regions' (digital) skill upgrading. Indeed, both regional convergence as well as the promotion of DS are at the top of the EU policy agenda. This is testified by the abundance of policy instruments explicitly aimed at strengthening the knowledge base of regions and at fostering structural convergence among them. We distinguish

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<sup>8</sup> In-depth analyses of the process of structural divergence between and within European economies is provided, among others, by Celi et al. (2018).

between EU funds that are directed at: i) strengthening EU's internal cohesion by supporting member states with a gross national income (GNI) per capita below 90% EU-27 average, i.e. the EUCF; ii) supporting member states' labor and social policies, including those directly related to the development of skills (e.g., training, reskilling, Life Long Learning programs), i.e. the ESF; iii) correcting imbalances between the development levels of EU regions including two specific programs aimed at supporting regional policies on research and digitalization, i.e. the ERDF. An overall positive effect of the abovementioned EU funds on the ability of regions to accumulate DS is expected<sup>9</sup>. However, relevant heterogeneities are also likely to emerge. For example, the ESF could be positively associated with the accumulation of DS, given the presence of programs that are explicitly aimed at supporting their diffusion at both the institutional and the labor market level. On the other hand, both the EUCF and the ERDF are expected to promote convergence, including in the domain of DS accumulation. This should be particularly true in the case of the ERDF, considering the growing importance of DS within this fund's priority actions<sup>10</sup>. However, expectations remain unclear about which fund is likely to contribute more to EU regions' DS accumulation. As a result, RQ3 is spelled out as follows:

**RQ3.** *Do European structural and regional funds (EUCF, ESF and ERDF) contribute to the diffusion and accumulation of DS across EU regions?*

All RQs are tested considering DS as a whole (baseline model) and distinguishing, as in Castellacci et al. (2020), between user, practitioner, and developer skills. The most reasonable expectation is that the more sophisticated the skills are (i.e. practitioner and developer) the more they are characterized by an heterogeneous and polarized distribution. This is mostly due to the (material, immaterial, individual and collective) costs that have to be borne in order to accumulate them as well as to their cumulative nature. By the same token, the more economically and technologically dynamic regions are expected to show superior performance particularly regarding practitioner and developer DS, given that the user DS tend to be easier to transfer and more transversely spread.

## 4. Data and descriptive evidence

This section illustrates the data sources used to analyze the diffusion of DS in Europe (Section 4.1) describing in-depth the indicators developed to measure EU regions' DS intensity (Section 4.2). Second,

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<sup>9</sup> A number of studies have focused on the impact of EU funds on regional growth and convergence (among the others, Crescenzi, 2009; Maynou et al. 2016; Psycharis et al. 2020). To the best of our knowledge, however, no contribution has yet focused on the relationship between EU funds and regions' DS endowment.

<sup>10</sup> For details on the ERDF's funding priorities, see: [https://ec.europa.eu/regional\\_policy/en/funding/erdf/](https://ec.europa.eu/regional_policy/en/funding/erdf/)

a set of descriptive statistics is provided mapping the diffusion of DS in Europe over the period distinguishing between user, practitioner and developer skills (Section 4.3). Third, relying on Transition Probability Matrices (TPM) the structural patterns of convergence/divergence between EU economies and regions are explored (Section 4.4).

## 4.1 Data

Data applied in this article stem from different sources: (i) the European Multilingual Classification of Skills, Competences, Qualifications and Occupations (ESCO); (ii) the European Labour Force Survey (EU-LFS); (iii) the European Regional Accounts (EU-REGIO); (iv) the OECD-REGPAT and (v) the Historical EU payments database.

ESCO is a European Commission project, run by the Directorate General Employment, Social Affairs and Inclusion (DG EMPL), providing a multilingual classification of European Skills, Competences, Qualifications and Occupations. It is aimed to identify and categorize skills, competences, qualifications and occupations relevant for the EU labour markets and education and training, in 25 European languages. In this sense, ESCO allows to match occupational profiles to skills, competences and qualifications.

The EU Labour Force Survey (EU-LFS) is the largest European household sample survey aimed to classify the population of working age (15 years and over) into three mutually exclusive and exhaustive groups: employed persons, unemployed persons and the population outside the labour force. EU-LFS provides labour market statistics for 35 participating countries over time. Individual data can be aggregated at the NUTS level since EU-LFS is stratified at the geographical level.

The European Regional Accounts (EU-REGIO) maintained by Eurostat provide a regional breakdown for major aggregates, such as gross value added (GVA) and household income. The OECD EPO-REGPAT is a comprehensive dataset providing all patent applications to the European Patent Office (EPO). We rely on inventors addresses to assign patents to all EU regions. Finally, the Historical EU payments database reports regionalised (NUTS-2) annual EU expenditure data (in current prices then transformed in 2015 prices) for specific EU funds including (ECF, ESF, ERDF).

Information from the above-mentioned sources have been merged at the NUTS2 level in order to have an integrated database at the European regional level covering 24 countries divided by 179 regions for 8 years (2011-2018)<sup>11</sup>. Table A1 in the Appendix shows the composition of the database.

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<sup>11</sup> Analyses are based on NUTS2 classification level for 2018-EU countries (excluding Finland, Malta, Poland and Bulgaria). In some cases, territorial aggregations had to be made at one digit level (Austria, the Czech Republic, Germany, Denmark, Croatia, Lithuania, Slovenia, Slovakia) or down to national level (Cyprus, Estonia, Luxembourg, the Netherlands, Latvia). Aggregations were necessary due to missing data at NUTS 2 level in the Labour Force Survey waves or to limitations resulting from changes in the NUTS classification over time.

## 4.2 Digital Skills Indicators

The key part of the analysis relies on the construction of the DSIs (Digital Skill Indicators) to proxy the level of “digitalization” of the local workforce. The main source for building DSIs is the v.1.0 release of ESCO. For almost 3,000 occupations (or job profiles), a detailed description of about 13,500 possible representative skills using unambiguous terminology in 25 languages is provided. Since the main aim of this work is to study the evolution and distribution of digital skills across European regions, we need to identify the bulk of skills associated with the use of digital technologies. To this purpose, we apply a three steps strategy. In a first stage, we analyze the textual description contained in ESCO for each skill that is potentially related to the use of digital technologies. As search criteria we rely on the dictionary words selected by Chiarello et al. (2018). Starting from 39 thousand semantic relations inherent to digital technologies, authors define the top 15 technologies for each of the 11 clusters identified using the algorithm described in Blondel et al. (2008). We improve this set of 161 words through the use of synonyms or alternative expressions (e.g. "data storage" as an alternative to "memory"), roots (e.g. "nanotec" clusters "nanotechnology", etc.) and acronyms (e.g. "CNC" as "Computer Numerical Controller") to end up with a selection of 75 items (Tab. 1 in appendix). In a second step, we define DS as a binary characteristic that takes the value 1 if at least one of the 75 keywords (defined in the first stage) is matched in the description and/or title of each competence of the ESCO, and 0 otherwise<sup>12</sup>.

Accordingly, we identify almost 1,200 ‘digital skills’ (DSKILL). Each DSKILL is then assigned to a category depending on the degree of professional expertise involved:

- user level (309 skills): requiring basic knowledge concerning how to use technology for very specific purposes; no specialist expertise needed;
- practitioner level (348 skills): requiring a certain degree of expertise to tailor technology and adapt it to the use context;
- developer level (546 skills): requiring significant expertise to design and modify technology.

As a second step, DSKILL are matched with each 4-digit ISCO occupations (429 individual occupations). Following Castellacci et al. (2018), we then build a digital skill indicator (DSI) for each 3-digit ISCO occupation relying on the following formula:

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<sup>12</sup> Notice that to build our occupation-level indicator we considered the absolute number of digital skills rather than the relative one (i.e. the ratio of DS over the total number of skills describing an occupation). By considering a relative measure, in fact, we would have risked underestimating the actual ‘digital content’ of more complex occupations characterized by a relatively larger number of skills.

$$DSI_j = \frac{\sum_{y=1}^{Y_j} DSKILLS_{y,j}}{N_y} \quad (1)$$

where the value of the DSI indicator for each 3-digit ISCO category  $j$  is equal to the sum of DS assigned to the related 4-digit ISCO occupations -  $DSKILLS_{y,j}$  - weighted by the number of employees belonging to such occupations -  $N_j$ <sup>13</sup>.

As a third step, we rely on (1) to derive a regional DS indicator. The following weighting procedure is carried out:

$$DSI_i = \sum_{j=1}^N (Nsh_{ij} * DSI_j) \quad (2)$$

where the regional  $DSI_i$  (2) -  $i \in \{NUTS2\}$  - is equal to the weighted average of (1) using the ISCO 3-digit employment shares -  $Nsh_{ij}, i \in \{NUTS2\}, j \in \{ISCO\ 3d\}$  - as weights. The latter is our key measure to assess diffusion and determinants of DS at the EU regional-level.

### 4.3 Mapping DS

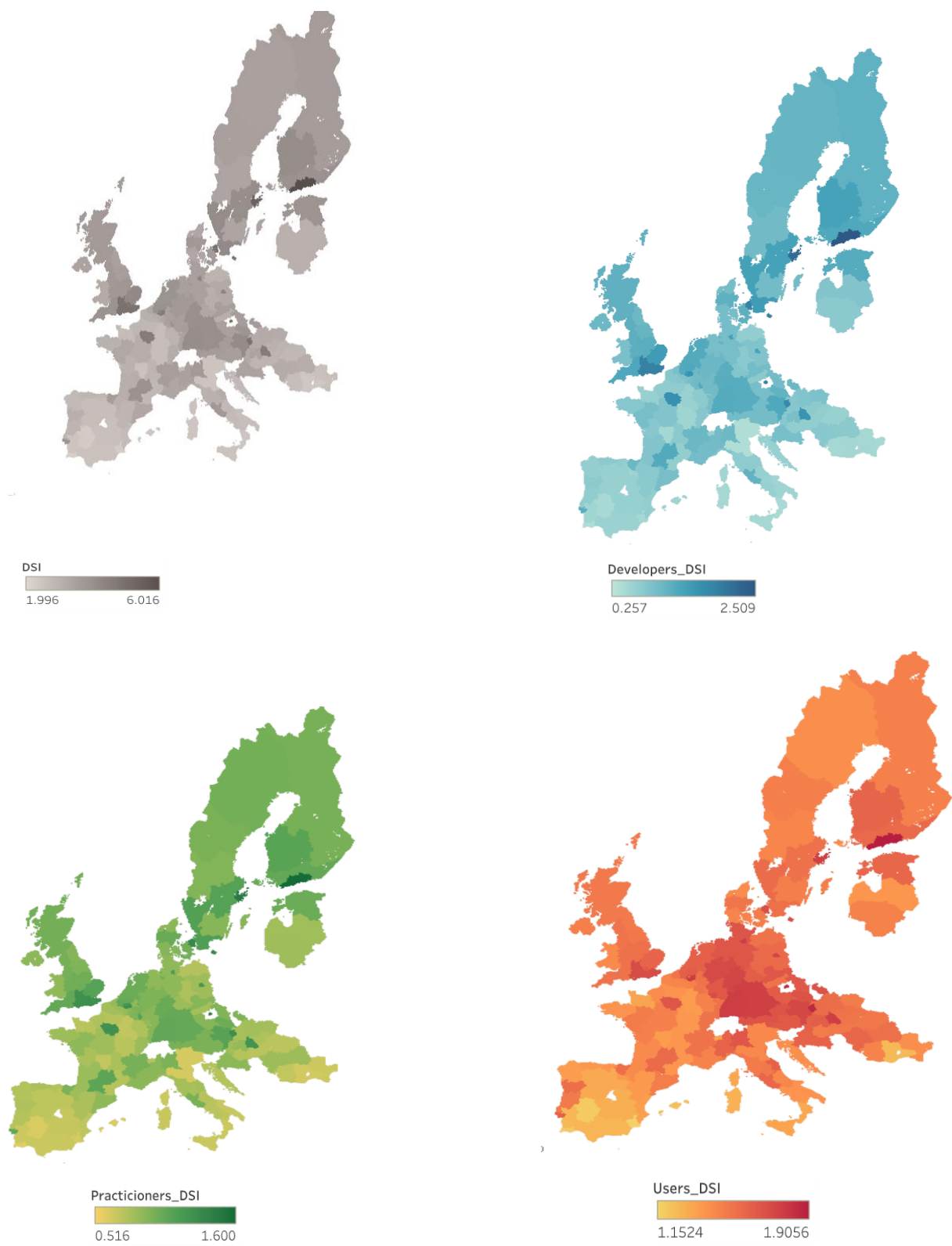
In what follow we assess the distribution of DS over time and across geographical areas. Figure 1 displays the diffusion of DS in the EU between the years 2011 and 2018. The level of digitalization of the workforce is highly heterogeneous across regions. This is not surprising, though. EU regions are in fact heterogeneous in terms of economic structures, labour market characteristics, education systems and sectoral compositions. From this point of view, the regional level represents a pertinent unit of analysis to investigate and understand the (asymmetric) diffusion of DS. Focusing on the broad DSI indicator (Figure 1), DS turn out to be significantly more concentrated in Northern EU regions, particularly Scandinavian ones, as compared to Southern Europe. Within-country heterogeneity matters too, however. In fact, non-negligible parts of France, Germany and Italy display a remarkable intensity in terms of DS. Again, a confirmation of the relevance of regional-level heterogeneities. Distinguishing between users, practitioners and developers allows unraveling additional evidence. Developers are relatively more concentrated in ‘affluent’ high-tech and service-oriented regions such as the London area in the UK, the Paris region (Ile-de-France), the south of Finland coinciding with the region of Helsinki,

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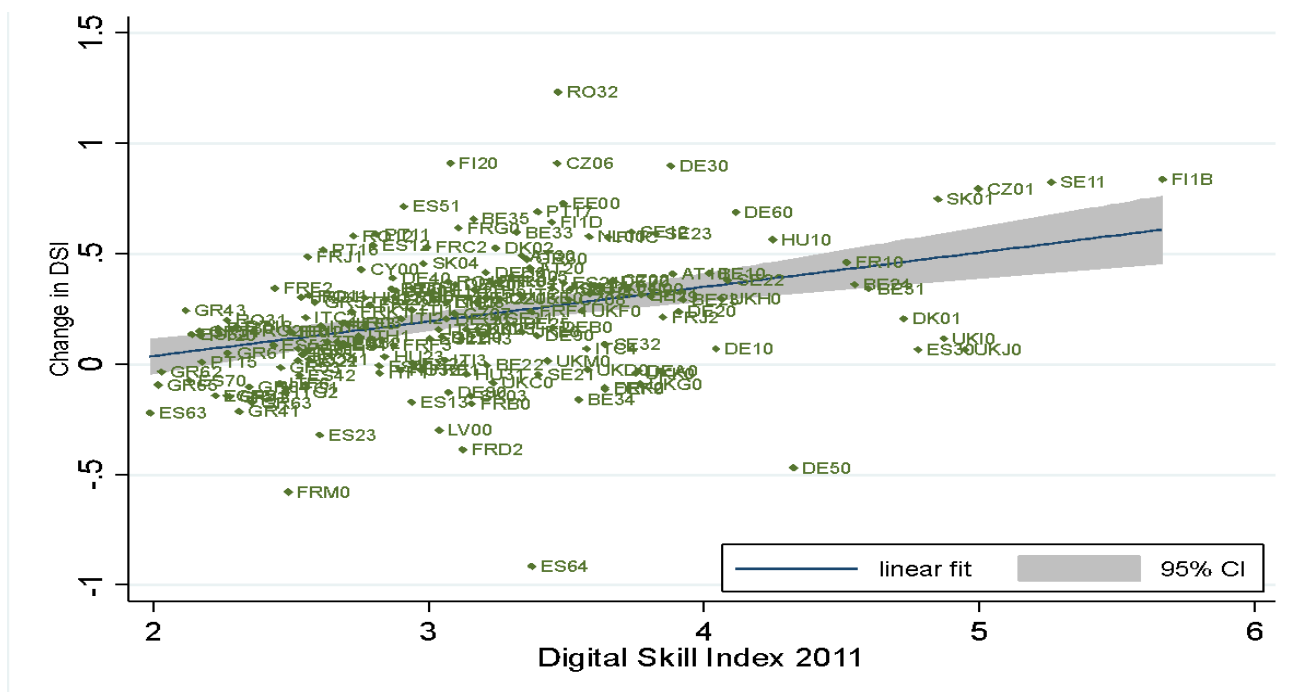
<sup>13</sup> The DSI has been then standardized to have zero mean and standard deviation equal to one.

the Stockholm area and, to a lesser extent, the Bayern region in Germany and north-west and central (Lazio) regions in Italy.

Figure 1. The DSIs across EU (NUTS-2) regions, annual average (2011-2018)

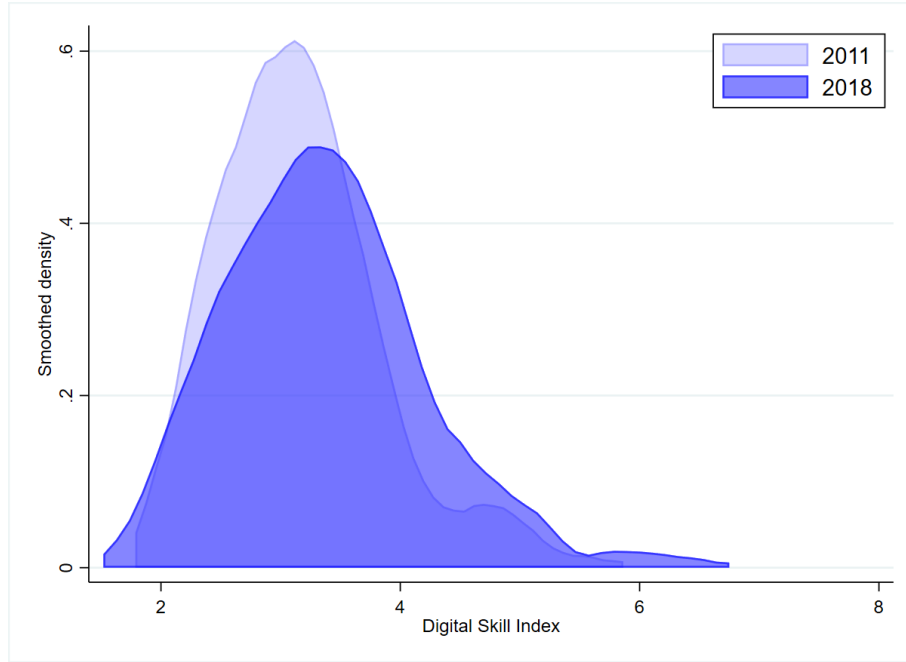


Concerning practitioners, a greater heterogeneity is detected. Overall, regions where capitals and big cities are located tend to outperform inner zones. On the other hand, Germany, Finland, Sweden, and the UK show a quite uniform diffusion of DS. Interestingly enough, users' DS seem to be mostly concentrated in the German core regions – i.e. central and north-West regions – and in few capital regions – the London area and the Helsinki region. Regarding the evidence on Germany, such concentration of users' DS may be associated to the strong manufacturing specialization of those regions. In fact, the growing digitalization of manufacturing supply chains could have fostered an analogously growing demand of 'blue-collar' digital competences. Do digital skills change over time? Can any convergence/divergence dynamics be detected? As a very preliminary answer to these questions, Figure 2 displays the association between DS indexes as measured in 2011 (initial year of the analysis) and changes over the 2011-2018 period. The scatter plot shows a slightly positive relationship between the two variables. Scandinavian regions show high initial level of digital competences as well as a steady growth between 2011 and 2018. The opposite holds for a number of Spanish (e.g., the Andalusia area) and Greek regions. Despite some 'digital divergence' seem to emerge, no clear-cut pattern can be detected, though. Most regions are in fact located in the middle part of the scatter plot displaying quite heterogeneous trajectories: for instance, while Berlin and Hamburg regions grow up faster, the Bremen area has fallen behind.



although the distribution is moving to the right suggesting a generalized DS upgrading in 2018 with respect to 2011, dispersion is also increasing lending support to the polarization hypothesis: regions that first accumulate tacit knowledge, digital competences, capabilities and related innovative capacity are likely to increase that advantage over time consolidating their positions<sup>14</sup>.

Figure 3. Distribution of the Digital Skill Index over time



#### 4.4 Structural dynamics

The diffusion of DS across EU regions is now further investigated relying on transition probability matrices (TPM). This allows capturing the degree of convergence/divergence among regions and, no less relevantly, the relative persistence of their ‘digital status’. As before, the analysis is carried for the broad DSI indicator and distinguishing between users, practitioners and developers.

We first briefly introduce the TPM methodology as applied to the DS case. Let’s consider  $i$  and  $j$  the event of being below and above the median value of DSI. The events could be approximated by a two-state Markov chain with transition probabilities:

$$P[X_t = i | X_{t-1} = j] = [p(1-p)(1-q)q] \quad (3)$$

The corresponding AR (1) process for the stochastic variable  $X_t$  is the following:

<sup>14</sup> In the Appendix figures A1, A2 and A3 show digital distributions for each specific indicator.



$$X_t = (1 - q) + \rho X_{t-1} + v_t$$

$$\text{where: } \rho = p + q - 1 \quad (4)$$

Each term of the (2x2) TPM will be the conditional probability  $p_{ij} = P(I_t = j | I_{t-1} = i)$ , or the probability of moving from state  $j$  to state  $i$ . Based on the estimated transition probabilities different situation are possible, in the case of two-dimensional matrix:

- i. Transient digitalization: if the sum of the lead diagonal terms is less than 1 there is no evidence of persistence;
- ii. Weak digitalization persistence: if the sum of the main diagonal terms is more than 1 but some of these terms are lower than 1/n (in this case 0.5);
- iii. Strong digitalization persistence, if the sum of the main diagonal terms is more than 1 and all the main diagonal terms are larger than 1/n (in this case 0.5).

The following table reports the TPMs for both broad DSI as well as developers, practitioners and users. More specifically, the main diagonal informs on the overall rate of persistence, while the second diagonal provides information about the relative importance of barriers to entry and exit. To better assess potential convergence/divergence patterns, we look at both Europe as a whole (first row of Table 1); as well as at the country groups (i.e. core, Southern periphery, Eastern Periphery and Northern/Scandinavian countries) proposed by the literature analyzing core-periphery polarization in the EU (see, among others, Celi et al. 2018). Overall, we find evidence of strong digitalization persistence as all terms of the main diagonal are larger than 0.5 and their sum is more than 1. This first evidence suggests the presence of intertemporal stability in the accumulation/diffusion of DS.

Table 1. TPMs across groups of countries

		DSI		DSI <i>developers</i>		DSI <i>practitioners</i>		DSI <i>Users</i>	
		Yes	No	Yes	No	Yes	No	Yes	No
All regions	Yes	0.94	0.06	0.94	0.06	0.94	0.06	0.91	0.09
	No	<b>0.10</b>	0.90	<b>0.11</b>	0.89	<b>0.10</b>	0.90	<b>0.11</b>	0.89
Core (AT; BE; DE; FR; LU; NL)	Yes	0.92	0.08	0.92	0.08	0.92	0.08	0.91	0.09
	No	<b>0.20</b>	0.80	<b>0.24</b>	0.76	<b>0.18</b>	0.82	<b>0.19</b>	0.81
East periph. (RO; HU; HR; SK; CZ; LV; LT)	Yes	0.94	0.06	0.90	0.10	0.92	0.08	0.94	0.06
	No	<b>0.12</b>	0.88	<b>0.14</b>	0.86	<b>0.11</b>	0.89	<b>0.17</b>	0.83
North & Sc. (SE; DK; FI; UK; EE; IE)	Yes	0.98	0.02	0.99	0.01	0.98	0.02	0.89	0.11
	No	<b>0.28</b>	0.72	<b>0.22</b>	0.78	<b>0.22</b>	0.78	<b>0.16</b>	0.84
South periph. (CY; GR; IT; PT; ES)	Yes	0.89	0.11	0.88	0.12	0.88	0.06	0.90	0.10
	No	<b>0.04</b>	0.96	<b>0.04</b>	0.96	<b>0.05</b>	0.94	<b>0.06</b>	0.94

While digitalization persistence seems to be widespread, some regions have more chances to move from a low towards a high digitalization path. This is the case of the so-called ‘core’ countries: Austria, Belgium, Germany, France, Luxembourg, and the Netherlands. On average, 20% of core regions moved from below to above the DSI median over the considered time span. This percentage grows to 24% when it comes to the more complex developers’ skills.

Regions located in the North and Scandinavian EU countries (Sweden, Denmark, Finland, the United Kingdom, Ireland and Estonia) perform even better: on average, 28% of them have shifted from a low to a high-digitalization path. Conversely, only 4% of Southern European regions have registered a transition over time: 5% for developers and 6% for users. Evidence from Table 1 suggests that intertemporal stability in digitalization effort and state dependency vary considerably across country groups. Regions located in the core and in Northern/Scandinavian countries have experienced a continuous upgrading while peripheral areas lagged behind. As a result, DS emerge as an additional driver of country and regional-level polarization confirming the evidence, regarding more traditional macroeconomic and technological performance indicators, provided, among others, by Grabner et al. (2020).

Table 2 replicates the exercise focusing on regions distinguished between those classified by the Commission as ‘target regions’ and receiving funds accordingly (during the 2007-2013 period); and those that have no access to these funds. This allows to further qualify our descriptive assessment relying on country groups that are explicitly related to policies directed at promoting convergence in the EU. As expected, target regions display lower transitions over time. Upon such a very preliminary descriptive inspection, therefore, it seems that being a target of EU funds is not as such a guarantee of DS upgrading.

Table 2. TPMs across groups of target regions (2007-2013)

		DSI		DSI <i>Developers</i>		DSI <i>Practitioners</i>		DSI <i>Users</i>	
Target regions		Yes	No	Yes	No	Yes	No	Yes	No
		0.93	0.07	0.86	0.13	0.87	0.13	0.92	0.08
No target region	Yes	<b>0.08</b>	0.92	<b>0.10</b>	0.90	<b>0.09</b>	0.91	<b>0.11</b>	0.89
	No	Yes	No	Yes	No	No	Yes	Yes	No
	Yes	0.94	0.06	0.95	0.05	0.95	0.05	0.91	0.09
	No	<b>0.12</b>	0.88	<b>0.11</b>	0.89	<b>0.10</b>	0.90	<b>0.12</b>	0.88

Finally, Table 3 shows the results once regions are classified according to terciles of the DSI. This allows capturing movements as well as persistence dynamics in a more detailed way. In fact, moving from the third to the first quantile is a rare opportunity: only a modest 0.2% of regions seem to perform such a jump. On the other hand, about 9% of regions moves from the second to the first quantile suggesting that having accumulated an ‘intermediate’ amount of digital competences may facilitate more substantial

upgrading. Further exercises are provided in Tables A3 and A4 in the Appendix where we evaluate transition probabilities at the top 15% and 25% of the DSI distributions.

Table 3. TPMs across terciles of the digital skill distributions

		First quantile	Second quantile	Third quantile
DSI	First quantile	0.87	0.12	0.005
	Second quantile	<b>0.09</b>	0.76	<b>0.15</b>
	Third quantile	<b>0.002</b>	<b>0.09</b>	0.91
DSI developers	First quantile	0.84	0.15	0.005
	Second quantile	<b>0.11</b>	0.74	<b>0.15</b>
	Third quantile	<b>0.002</b>	<b>0.10</b>	0.89
DSI practitioners	First quantile	0.87	0.13	0.002
	Second quantile	<b>0.09</b>	0.79	<b>0.12</b>
	Third quantile	<b>0.005</b>	<b>0.07</b>	0.93
DSI users	First quantile	0.86	0.13	0.005
	Second quantile	<b>0.12</b>	0.75	<b>0.13</b>
	Third quantile	<b>0.002</b>	<b>0.10</b>	0.89

## 5. Empirical strategy and results

As a further step of the analysis we explore the probability of regions to move from backwardness to digital upgrading through a multivariate approach controlling, simultaneously, for both structural factors, influencing on the one hand the diffusion of digital skills and the strengthening of regional capabilities, and EU funds, potentially affecting digital infrastructure endowments. As for innovation capabilities, DS might display high persistence over time as clearly depicted in paragraph 4. To incorporate this crucial element in our econometric analysis, we rely on a discrete choice panel data model based on the estimator proposed by Wooldridge (2005) and applied, among others, by Peters (2008) and Antonelli et.al (2012). While the TPM exercise provided a useful background picture concerning the relative persistence of regional DS divides, the following analysis allows identifying the actual influence of past digital skills adoption on the subsequent regional digital skills intensity, after controlling for relevant structural factors and EU funding.

The analysis is based on a *dynamic discrete choice model* in which the dependent variable is regressed against its past realization ( $t-1$ ), its initial value ( $t_0$ ) and a set of relevant controls  $X_i$  including, for each region  $i$ , information regarding sectoral composition, average firm size, labor market characteristics and competences, technological capabilities (more details are provided in what follows). The dependent variable (DSKILL) is a dummy variable assuming value one in period  $t$  if a region is above the median of the DSI; and 0 if it is positioned below the median. Our goal is to capture ‘true state dependence’ in terms of regions’ DS accumulation controlling, as much as possible, for endogeneity sources related to observable and unobservable heterogeneity. In particular, endogeneity may arise due to the correlation between regions’ DS endowments – proxied by DSI at  $t_0$  - and unobservable elements which may explain

long-term structural differences concerning regions' economic, technological and skill-related dynamism. To partly solve this problem, we rely on the procedure proposed by Wooldridge (2005), specifying the distribution of the unobserved component  $u_i$  conditional on DSI at  $t_0$  and on the region-specific time average of the controls included in  $X_i$ . In other words, we use the first realisation of the DS indicator ( $DSI_{i,0}$ ) and the time-averaged covariates ( $\bar{X}_i$ ) as predictors of the individual (regional) effect. The estimated model can thus be written as follows:

$$DSKILL_{i,t} = \alpha + \theta DSKILL_{i,t_0} + \gamma DSKILL_{i,t-1} + \beta X_{i,t} + \delta \bar{X}_i + \varepsilon_{i,t} \quad (5)$$

where for each region  $i$  and year  $t$  the dummy  $DSKILL_{i,t}$  is regressed against its initial value ( $DSKILL_{i,t_0}$ ), its first lag ( $DSKILL_{i,t-1}$ ), the matrix of covariates ( $X_{i,t}$ ) and their region-specific time average ( $\bar{X}_i$ ). The matrix  $X$  includes a first set of structural variables related to the region's productive structure: (i) share of employees in high-tech and knowledge intensive services as defined by OECD; (ii) share of employees in large and small companies. A second set of variables has to do with workforce composition and job characteristics: (iii) share of employees with tertiary education; (iv) share of young workers; (v) share of workers having permanent contracts; (vi) share of non-EU workers. A third set of variables, in turn, refers to technological and macroeconomic characteristics proxied by vii) the number of patents per habitant; and viii) the value added per employee (in logarithm). Finally, a specific test is run including three variables related to EU funds (see Table 5A for descriptive statistics of variables included in the analysis): ix) EUCF, ESF and ERDF. Notice that all models have been estimated clustering standard errors at the regional (NUTS2) level.

## 5.1 Results

Table 6 shows the results for different specifications of the model regarding the general DSI (column 1) as well as the specific measures for developers (column 2), practitioners (column 3) and users (column 4). We report the models estimated with the Wooldridge approach (see above). Results support the thesis of high persistence of digital skills since, even after controlling for all the structural factors included in  $X$ , the probability of observing an upgrading in digital skills (that is, a transition from below-the-median to above the median DSI) in period  $t$  is still positively and significantly affected by its previous realization. In other words, having high digital capabilities in the previous period is, all things being equal, a strong and significant predictor of the current DS status. Initial conditions matter too. The coefficient associated to the initial value of DSI is in fact positively and significantly correlated to the dependent variable, all across specifications. However, when we run the analysis distinguishing between users, practitioners and

developers, interesting differences arise. In particular, while persistence is detected with respect to users and digital developers' skills, the opposite holds for practitioners. This result is probably influenced by the peculiar distribution of regions in this specific indicator with respect to the other two cases. As shown in Fig.1A-2A-3A, the distribution of regions for practitioners' DS is less dispersed and more concentrated around the mean, implying that state changes are more probable for this category than for the others. Overall, these results provide a positive answer to our **RQ1**. The diffusion of DS across EU regions turns out to be characterized by divergence and polarization. A potential explanation may point to the well-known path-dependent nature of digital technologies and competences as well as to the largely documented between and within-country structural polarization affecting the European economy (Celi et al. 2018). A polarization that indeed emerges also looking at DS types, particularly concerning users and developers' skills. Regions located at the top and bottom of the conditional DSI distribution are in fact very much likely to keep their status despite the number of economic, technological and labor market heterogeneities that are controlled for.

The inclusion of a large set of controls allows to test the robustness of the relationships identified between past and current realization of the digital skill indicators. Turning, therefore, to our **RQ2** - *What are the structural factors contributing the most to the diffusion of DS across EU regions?* – we can assess that, among most important factors, the share of employees in high-tech manufacturing and knowledge intensive services plays a crucial role, except for digital users. This is not surprising, though. Regions where most of the high-tech manufacturing and knowledge intensive activities are concentrated are also likely to show a relatively more intense demand for practitioners and developers' DS. Basic DS, as those related to the use of common digital artifacts, are in turn more widespread across sectors and regions. This evidence is coherent with the polarization between core and Northern EU regions, where most of the high-tech manufacturing and services are concentrated, documented in Section 4.

Similar arguments may apply concerning the positive and significant role of firm size. Since Schumpeter, it is common knowledge that large firms are the *loci* where high skills tend to be accumulated. And DS are no exception. Several research papers exploring firm-level data (Calvino et al., 2022; Müller et al., 2021; Cirillo et al., 2021) have highlighted that large companies have a significantly higher probability to adopt digital technologies due to their relatively stronger absorptive capacity. Our results support this view highlighting that regions where there is higher concentration of large companies are also favored in terms of DS accumulation, particularly when it comes to developers and practitioners' skills.

Regarding the accumulation of skills, including digital ones, education is of course the most obvious predictor. This is confirmed by our estimations: regions showing a relatively higher share of tertiary educated workers are also better positioned in terms of DS, in particular with regard to developers and practitioners. Indeed, the possibility to fully exploit the potential of digital technologies, for instance in

terms of labour productivity, depends among other factors on the availability of specific skills and competences usually associated to tertiary education.

Finally, demand seem to matter too. A higher valued added per employee is also a strong predictor of DS accumulation with respect to the broad indicator. When specific digital profiles are distinguished, it turns out that the ‘demand-pull’ effect plays a role only in the case of practitioners while no significance is detected concerning users and developers.

Hence, the empirical evidence so far explored emphasizes three main key factors that are likely to shape EU regions’ dynamics in terms of DS: (i) concentration of large and high-tech/knowledge intensive businesses; (ii) presence of a qualified workforce able to virtuously interact with digital technologies; (iii) a sustained aggregate demand. This suggests that the diffusion of DS in European regions follows a process which is both *past* and *path* dependent. As previously highlighted past conditions are relevant and robust and tend to favor regional divergence and polarization processes. However, contingent factors are able to affect the direction and the dynamics of the digitalization path followed by regions, suggesting that some form of convergence can be attained when proper actions are put in place over time.

Table 6. Marginal effects of dynamic random effects probit model with unobserved heterogeneity. Dependent variable: High digital skill regions (0/1) – above the median

	DSI	Developers	Practitioners	Users
	(1)	(2)	(3)	(4)
	b/se	b/se	b/se	b/se
High DSI (lag)	0.073** (0.031)			
High DSI (first period)	0.209*** (0.037)			
High DVP (lag)		0.054** (0.026)		
High DVP (first period)		0.173*** (0.035)		
High PCT (lag)			-0.018** (0.008)	
High PCT (first period)			0.270*** (0.008)	
High DSI Use (lag)				0.063* (0.036)
High DSI Use (first period)				0.314*** (0.059)
Share of employees in HT and KIS	0.011* (0.006)	0.020*** (0.006)	0.006** (0.003)	0.008 (0.006)
Share of employees in large firms	0.231 (0.392)	0.818*** (0.268)	0.407** (0.192)	-0.072 (0.331)
Share of employees in small firms	-0.184 (0.835)	0.697 (0.766)	0.345 (0.447)	-0.620 (0.867)
Share of tertiary educated workers	1.195*** (0.311)	0.873** (0.344)	0.892*** (0.253)	0.528 (0.466)
Share of workers with permanent jobs	-0.108 (0.356)	-0.171 (0.379)	-0.011 (0.184)	-0.005 (0.428)
Share of non-EU workers	-0.532 (0.774)	0.087 (0.881)	-1.055 (0.642)	-2.823** (1.228)
Share of young workers	-0.054 (0.362)	-0.002 (0.333)	-0.170 (0.212)	-0.373 (0.367)

Value Added per employee (log)	0.568** (0.263)	0.298 (0.199)	0.353*** (0.103)	-0.113 (0.331)
Number of patents/pop	249.233 (293.535)	286.091 (298.029)	98.004 (190.782)	-346.505 (257.595)
Average Share of employees in HT and KIS	-0.012* (0.007)	-0.017*** (0.006)	-0.005 (0.003)	-0.006 (0.007)
Average Share of employees in Large firms	-0.277 (0.424)	-0.850** (0.348)	-0.657*** (0.214)	0.340 (0.375)
Average Share of employees in small firms	-0.698 (0.703)	-1.855*** (0.676)	-1.538*** (0.361)	0.080 (0.801)
Average Share of tertiary educated workers	-1.245*** (0.339)	-0.783** (0.395)	-0.855*** (0.271)	-0.652 (0.564)
Average Share of workers with permanent jobs	0.951** (0.453)	1.083** (0.445)	0.939*** (0.194)	0.483 (0.500)
Average Share of non-EU workers	0.827 (0.820)	0.049 (0.888)	1.371** (0.640)	2.757** -1.106
Average Share of young workers	0.228 (0.492)	0.853* (0.453)	0.128 (0.248)	0.227 (0.814)
Average Value Added per employee (log)	-0.588** (0.266)	-0.292 (0.216)	-0.446*** (0.103)	0.019 (0.363)
Average Number of patents/pop	1084.157** -440.133	1137.855** -472.902	1596.099*** -242.674	786.703 -669.866
Obs	1159	1159	1159	1159
Wald chi2(36)	193.91	153.31	299.86	117.69
Prob > chi2	0.0000	0.0000	0.0000	0.0000
sigma_	0.8608	11.213	3.2238	1.5540
S.E. (sigma)	0.2249	0.2563	0.3817	0.6737

Note: Clustered robust standard errors in parentheses.

In this respect, it appears to be of interest investigating how European structural and regional funds may shape the diffusion and accumulation of DS (**RQ3**). In order to provide an answer to this question, we enrich the empirical model specified in (5) including of three variables proxying the amount spent per inhabitant by three specific European funds (EUCF, ESF and ERDF).

It is worth to recall that the EUCF targets only the weakest member states, i.e. whose gross national income per inhabitant is less than 90% of the EU average. It aims to reduce economic and social disparities and to promote sustainable development, mainly by supporting investment in the field of transport infrastructure and environment. The ESF supports investments to promote employment, human capital and social cohesion. Finally, the ERDF focuses its investments on key priority areas. This is known as 'thematic concentration', which increases with the degree of development of EU regions and regards, in particular, innovation and research, the digital agenda; support for small and medium-sized enterprises (SMEs); the low-carbon economy<sup>15</sup>.

Table 7 clearly shows that the inclusion of the three funds does not alter the main relationships already sketched in Table 6, overall confirming the presence of persistence patterns across regions in terms of relative DS intensity. When looking at the broad DSI indicator, results show that only regions benefitting

<sup>15</sup>These are the ERDF 2014-2020 specific thematic areas, but similar areas such as research, innovation, environmental protection and risk prevention were covered by the previous programme (2007-2013).

from EUCF tend to benefit in terms of higher digital capabilities. On the contrary, both coefficients associated with ESF and ERDF do not show any statistically significant effect. This result, although does not represent robust evidence of the existence of a causal nexus between the considered variables, offers interesting insights that can be further scrutinized in more dedicated analyses. In particular, it is worth underlining that the EUCF – the only EU fund among those considered that is exclusively targeted to the weakest regions – turns out to be the more significant form of support for regions trying to pursue a DS upgrading. On the contrary, while other funds might have a positive effect on the overall process of digitalization of EU regions, they appear to be not particularly effective in shaping a process of convergence between core and periphery regions in terms of DS accumulation. This is even more clear when the specific DS categories of digital skills are analyzed. Results show that the statistical significance of the EUCF variable is mainly driven by its effect on the group of users, which sounds reasonable as it attains to the more basic domain of digital skills, on which the weakest regions can more easily realize a catch-up process. Moreover, while for the group of users, the coefficient relative to the ESF turns out to be (barely) positively significant, the one associated with the ERDF is found to be negative and statistically significant. A possible interpretation of this outcome is, on the one hand, that regions receiving a greater amount per capita of ESF, were able to benefit of dedicated resources on skills and human capital which is a main target of this type of support program. On the other, the greater concentration (and effective use) of resources on key areas, including innovation and digital transformation, which is required by law for the most developed regions with respect to less advanced ones, might have exerted a divergence rather than a convergence effect. This might explain why those weakest regions receiving a greater level of ERDF per capita increase their relative distance in terms of users of digital skills with respect to most advanced regions.

Table 7. Marginal effects of dynamic random effects probit model with unobserved heterogeneity. Dependent variable: High digital skill regions (0/1) – above the median

	DSI	Developers	Practitioners	Users
	b/se	b/se	b/se	b/se
High DSI (lag)	0.074** (0.031)			
High DSI (first period)	0.191*** (0.037)			
High DVP (lag)		0.057** (0.026)		
High DVP (first period)		0.154*** (0.034)		
High PCT (lag)			-0.032** (0.013)	
High PCT (first period)			0.242*** (0.013)	
High DSI Use (lag)				0.047** (0.019)
High DSI Use (first period)				0.296*** (0.019)



Share of employees in HT and KIS	0.011*	0.021***	0.008**	0.006
	(0.006)	(0.007)	(0.004)	(0.006)
Share of employees in large firms	0.212	0.925***	0.480**	0.092
	(0.425)	(0.290)	(0.226)	(0.318)
Share of employees in small firms	0.168	0.939	0.559	-1.231
	(0.840)	(0.767)	(0.558)	(0.908)
Share of tertiary educated workers	1.348***	0.983**	1.080***	0.782*
	(0.348)	(0.435)	(0.288)	(0.473)
Share of workers with permanent jobs	0.073	-0.115	0.022	-0.272
	(0.406)	(0.453)	(0.236)	(0.479)
Share of non-EU workers	-0.494	0.070	-1.514**	-3.189***
	(0.765)	(0.888)	(0.723)	(0.922)
Share of young workers	-0.025	-0.064	-0.442*	-0.166
	(0.397)	(0.375)	(0.261)	(0.428)
Value Added per employee (log)	0.667**	0.305	0.626***	-0.120
	(0.289)	(0.224)	(0.131)	(0.346)
Number of patents/pop	321.650	345.464	228.200	-376.666
	(285.233)	(287.697)	(262.087)	(252.787)
<b>ERDF Funds</b>	<b>-0.001</b>	<b>-0.001</b>	<b>-0.000</b>	<b>-0.008***</b>
	<b>(0.002)</b>	<b>(0.002)</b>	<b>(0.000)</b>	<b>(0.003)</b>
<b>CF Funds</b>	<b>0.004**</b>	<b>-0.000</b>	<b>0.003</b>	<b>0.013**</b>
	<b>(0.002)</b>	<b>(0.002)</b>	<b>(0.002)</b>	<b>(0.005)</b>
<b>ESF Funds</b>	<b>-0.000</b>	<b>0.007</b>	<b>0.005</b>	<b>0.003*</b>
	<b>(0.004)</b>	<b>(0.005)</b>	<b>(0.004)</b>	<b>(0.001)</b>
Average Share of employees in HT and KIS	-0.010	-0.014**	0.000	-0.011
	(0.007)	(0.007)	(0.004)	(0.007)
Average Share of employees in large firms	-0.084	-0.802**	-0.208	0.143
	(0.450)	(0.352)	(0.245)	(0.366)
Average Share of employees in small firms	-1.037	-2.224***	-2.173***	0.274
	(0.706)	(0.679)	(0.404)	(0.728)
Average Share of tertiary educated workers	-1.342***	-0.895*	-1.028***	-0.692
	(0.370)	(0.480)	(0.299)	(0.492)
Average Share of workers with permanent jobs	0.446	0.593	0.018	0.913*
	(0.492)	(0.495)	(0.248)	(0.508)
Average Share of non-EU workers	0.758	-0.025	2.194***	3.139***
	(0.816)	(0.901)	(0.710)	(0.941)
Average Share of young workers	-0.137	0.533	-0.064	0.464
	(0.535)	(0.483)	(0.304)	(0.547)
Average Value Added per employee (log)	-0.660**	-0.332	-0.774***	0.105
	(0.277)	(0.223)	(0.136)	(0.345)
Average Number of patents/pop	870.290**	869.247**	1830.870***	1051.109***
	-408.444	-423.269	-331.086	-344.272
Average ERDF Funds	0.001	0.002	0.003***	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Average CF Funds	0.008	0.010*	0.017***	-0.002
	(0.005)	(0.006)	(0.003)	(0.005)
Average ESF Funds	-0.012**	-0.029***	-0.027***	0.006**
	(0.006)	(0.010)	(0.006)	(0.002)
Observations	1159	1159	1159	1159
Wald chi2(36)	212.37	180.97	196.96	215.40
Prob > chi2	0.0000	0.0000	0.0000	0.0000
sigma_	0.7532	0.9346	2.9743	2.0195
S.E. (sigma)	0.2368	0.2277	0.4238	0.2696

Note: Clustered robust standard errors in parentheses.

## 6. Conclusions

This study provides new empirical evidence on regional patterns of digitalization in Europe during the decade 2011-2018. In particular the analysis focused on the distribution of DS across EU regions, by developing a regional digital skill index (DSI) starting from the ESCO taxonomy. The DSI is a synthetic measure of the local DS endowment of EU regions and basically reflects the occupational composition of regions based on the degree of digitalization knitted within the employed workforce. The paper offers a rich set of descriptive evidence based on the regional distribution of the DSI, as well as an econometric analysis which allowed us to appreciate the actual role of structural elements and EU policies in shaping the *path* of regional digital upgrading while controlling for the *past* dependency of such phenomenon.

While further analyses could provide more robust evidence on the causal relationships between the considered variables, and identify proper net effects associated with EU policies, our empirical analysis offers new insights on the presence of a strong persistence affecting regional digital performances. A finding confirming the deep polarization across EU regions in the diffusion of digital skills, which parallels those in terms of development of economic activities, institutional and societal infrastructures. Moreover, we identify the key enablers for DS upgrading at regional level. In this regard, the relevance at the regional level of knowledge-intensive industries and services represents an important condition for shaping the local use of high-skilled job profiles associated with more advanced DS (i.e. *developers* and *practitioners*). In addition, superior performances in terms of regional DSI are positively associated with the presence of large companies, as they tend to benefit of better conditions in terms of financial resources, internal cognitive resources, organisational and managerial capabilities, to invest and implement advanced, cutting-edge digital technologies.

Furthermore, we investigated the link between EU policies and the intensity of use of digital skills. In particular, we found a positive correlation between EUCF and superior regional DSI performance. Similarly, the ESF turns to be an effective lever of the digital upgrade, but statistically weaker if compared to the EUCF. Both, EUCF and ESF, positively influence the diffusion of 'digital-friendly' occupations related to basic and elementary digital skills, as they have among their objectives to support employment, help people find better jobs and ensure more equal employment opportunities, paying particular attention to the less skilled workforce, such as young people and the long-term unemployed (Colnot and Pellegrin, 2019). On the contrary, we detect a negative and statistically significant link between the ERDF, and above median DSI-*users* indicator.

Building on these results, the analysis suggests that regional convergence, also with respect to digital performance, is still a goal far from being achieved. Undoubtedly, the pandemic has accelerated the digitalization process across regions, but the digital polarization between and within countries remains. However, the proposed analysis offers some indication on the direction to be pursued in order to reverse the polarization trend and open up a path of (digital) rebalancing across regions. In particular, policies promoting the high education sector and the local availability of digital competences, as well as structural

changes enabling the local development of knowledge-intensive sectors, favoring the growth of firms' dimension and improving infrastructural conditions appear to be relevant.

In this direction, the national Recovery and Resilience Plans (RRPs) represent the main policy tool to achieve the digital transition, with almost of 26% of the spending allocated, to date, to the digital transition. Based on the EU's broadband strategy to lead "Gigabit society" by 2025, many RRP's provide actions to ensure the right environment and conditions for the deployment of advanced digital – very high-capacity – networks (i.e. Gigabit connectivity, 5G coverage, Internet connectivity at least 100Mbps) among key adopters (i.e. schools, hospitals, public administrations, terrestrial transport path, enterprises and households) and rural and remote areas. This is a pre-condition to close the digital gaps across Europe, but complementary policy actions have to be launched to effectively achieve this goal. For instance, policy support should positively influence the demand-side of digital adoption, especially regarding firms. In this respect we notice that many industrial plans implemented in the context of RRP's are based on individual fiscal benefit (i.e. tax credit) to promote digital investments in the framework of Industry 4.0. Based on this mechanism, the territorial distribution of public resources follows a spontaneous path that basically mirrors the spatial location of the productive base. This means that less developed areas, such as the Italian Mezzogiorno and other peripheral areas of Europe, are not provided with the right conditions, in both quantitative and qualitative terms, to maximize the potential of the digital transformation. This implies that, in these areas, firms are, on average, weaker concerning their economic, technological and organizational profiles. These conditions, taken together, hamper the uptake of digital solutions by the private sector, slowing down the overall digital performance of the region. To remove these barriers, industrial policy measures aimed at enlarging and enhancing the local productive base should complement the actions on broadband infrastructures. With specific regard to the local workforce, less developed or declining areas often give rise to young and, not infrequently, highly skilled workers who move to richer regions or countries to find better job opportunities. In this context, increasing the demand for advanced (digital) skills to be employed in local public and private organizations would mitigate the migration process and favor the digital upgrading, with an increase in aggregate competitiveness and an improvement in the quality of both private initiatives and public services. This must go hand in hand with a more systemic and holistic logic, in which LIS (or RIS) can perform as 'digital hubs' where advanced industries and knowledge-intensive services interact with higher education institutions and qualified public administrations.

## Appendix

Table 1A. List of digital keywords.

.Net	Decision Support System	Programming
3D	Digital Signal	Radio Frequencies
Algorithm	Dos	Radio Service
Android	Fleet Management	Real-Time Computing
Application Programming Interface (API)	Global Positioning System	Robotics
Artificial Intelligence	Html	Router
Automated Optical Inspection (AOI)	Human-Computer Interaction	Routing Protocol
Automation	Ibm	Semantic
Barcode	Intel	Semiconductor
Beacon	Internet	Semiotic
Big Data	Ios	Sensor
Business Intelligence	Keyword	Server
Circuit Board	Laptop	Smart Machine
Cloud	Laser	Smart Meter
CMOS	Linux	Speech Recognition
CNC (Computer Numerical Controlled)	Machine Learning	System Operation
Coding	Memory	Tablet
Computer	Microsys	Telemetry
CPU	Middleware	User Interface
Crypt	Nanotec	Virtual Machine
Cyber	Operating System	Virtual Reality
Data Analysing	Perl	Visual Basic
Data Mining	Predictive Models	Web
Data Model	Printed Circuit	Wireless
Data Storage	Programmable Logic Controller (PLC)	Xml

Fig.1A Digital skill index for developers over time

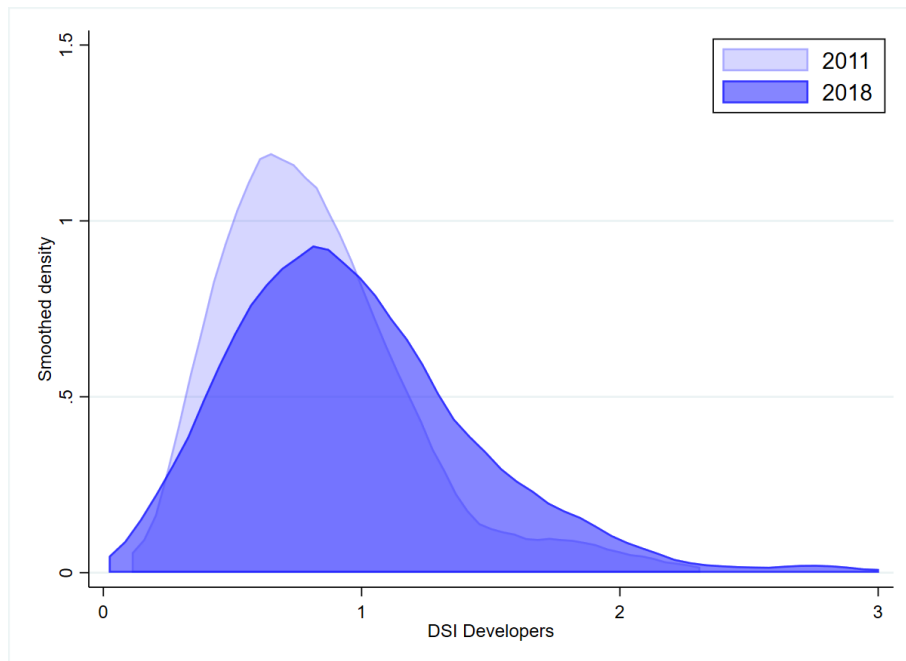


Fig.2A Digital skill index for practitioners over time

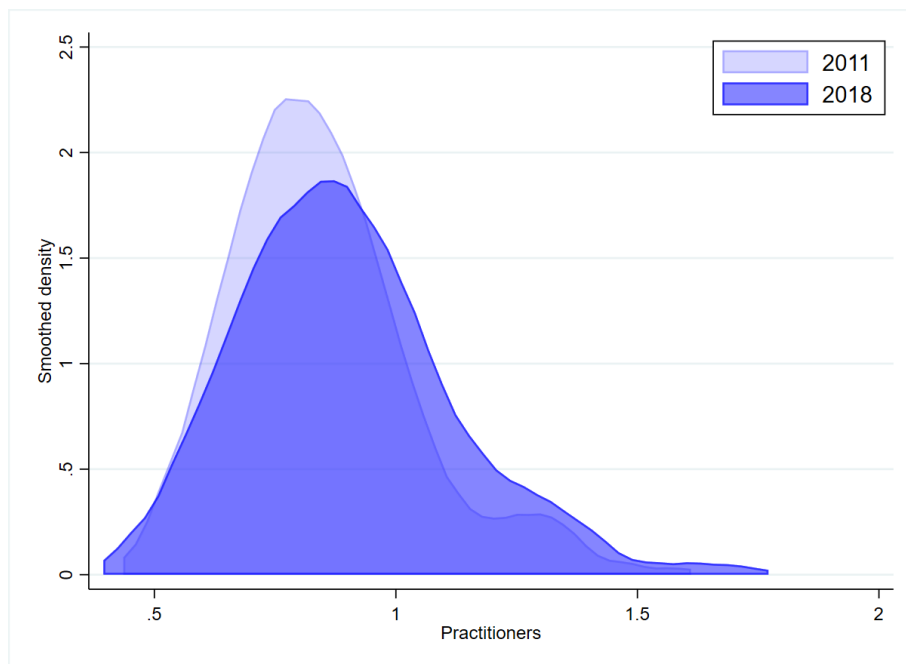


Fig.3A Digital skill index for users over time

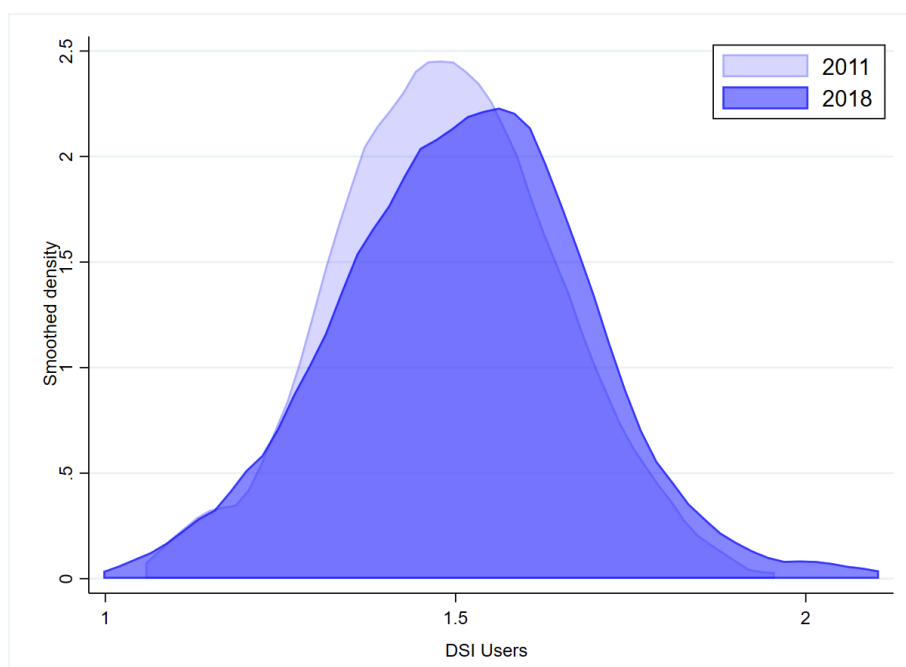


Table 2A. Composition of the database (numbers of regions for each country)

COUNTRY	2011	2012	2013	2014	2015	2016	2017	2018	TOTAL
AT	3	3	3	3	3	3	3	3	24
BE	11	11	11	11	11	11	11	11	88
CY	1	1	1	1	1	1	1	1	8
CZ	8	8	8	8	8	8	8	8	64
DE	16	16	16	16	16	16	16	16	128
DK	5	5	5	5	5	5	5	5	40
EE	1	1	1	1	1	1	1	1	8
ES	19	19	19	19	19	19	19	19	152
FI	5	5	5	5	5	5	5	5	40
FR	22	22	22	22	22	22	22	22	176
GR	13	13	13	13	13	13	13	13	104
HR	2	2	2	2	2	2	2	2	16

HU	7	7	7	7	7	7	7	7	56
IE	2	2	2	2	2	2	2	2	16
IT	21	21	21	21	21	21	21	21	168
LT	1	1	1	1	1	1	1	1	8
LU	1	1	1	1	1	1	1	1	8
LV	1	1	1	1	1	1	1	1	8
NL	1	1	1	1	1	1	1	1	8
PT	7	7	7	7	7	7	7	7	56
RO	8	8	8	8	8	8	8	8	64
SE	8	8	8	8	8	8	8	8	64
SK	4	4	4	4	4	4	4	4	32
UK	12	12	12	12	12	12	12	12	96
<b>TOTAL</b>	179	179	179	179	179	179	179	179	1,432

Table 3A. TPMs for top 15% of the digital skill distributions

	DSI		DSI <i>developers</i>		DSI <i>practitioners</i>		DSI <i>users</i>	
	Yes	No	Yes	No	Yes	No	Yes	No
Yes	0.88	0.11	0.89	0.10	0.90	0.10	0.87	0.12
No	<b>0.04</b>	0.96	<b>0.04</b>	0.96	<b>0.03</b>	0.96	<b>0.03</b>	0.97

Table 4A. TPMs for top 25% of the digital skill distributions

	DSI		DSI <i>developers</i>		DSI <i>practitioners</i>		DSI <i>users</i>	
	Yes	No	Yes	No	Yes	No	Yes	No
Yes	0.90	0.10	0.89	0.10	0.92	0.08	0.91	0.09
No	<b>0.06</b>	0.94	<b>0.05</b>	0.95	<b>0.04</b>	0.96	<b>0.04</b>	0.96

Table 5A. Descriptive statistics of main variables.

	Min	Max	Mean	SD
Share of employees in HT and KIS	13.2	62.6	39.94	9.06
Share of employees in large firms	0.01	0.53	0.33	0.11
Share of employees in small firms	0	0.30	0.03	0.04
Share of tertiary educated workers	0.11	0.62	0.31	0.10
Share of workers with permanent jobs	0.35	0.96	0.70	0.10
Share of non-EU workers	0	0.53	0.06	0.06
Share of young workers	0.36	0.70	0.55	0.04
Value Added per employee (log)	9.02	11.69	10.78	0.48
Number of patents/pop	0	0.000598	0.0000837	0.000101
Average Share of employees in HT and KIS	14	61.61	40	8.93
Average Share of employees in large firms	0.03	0.51	0.33	0.11
Average Share of employees in small firms	0	0.16	0.031	0.037
Average Share of tertiary educated workers	0.12	0.58	0.31	0.09
Average Share of workers with permanent jobs	0.39	0.94	0.70	0.102
Average Share of non-EU workers	0.00	0.51	0.06	0.06
Average Share of young workers	0.46	0.68	0.55	0.037
Average Value Added per employee (log)	9.15	11.66	10.80	0.46
Average Number of patents/pop	0	0.0004431	0.0000837	0.0000961
ERDF Funds	0	288.60	6.39	15.43
CF Funds	0	31.95	2.01	4.46
ESF Funds	0	79	2.83	5.94
Average ERDF	0.08	64.28	6.39	9.77
Average CF	0	14.47	2.02	3.64
Average ESF	0.11	42.02	2.83	4.70

Table 6A. Marginal effects of dynamic random effects probit model with unobserved heterogeneity. Dependent variable: High digital skill regions (0/1) – Top 25%

	DSI	Developers	Practitioners	Users
	b/se	b/se	b/se	b/se
High DSI (lag)	0.050 (0.035)			
High DSI (first period)	0.232*** (0.040)			
High DVP (lag)		-0.000 (0.011)		
High DVP (first period)		0.186*** (0.011)		
High PCT (lag)			0.027*** (0.009)	
High PCT (first period)			0.170*** (0.008)	
High DSI Use (lag)				0.085*** (0.025)
High DSI Use (first period)				0.218*** (0.025)
Share of employees in HT and KIS	0.003 (0.005)	0.007* (0.004)	0.002 (0.004)	-0.002 (0.007)
Share of employees in Large firms	0.293 (0.372)	0.034 (0.268)	0.177 (0.250)	0.413 (0.346)
Share of employees in small firms	-0.338 (2.146)	-1.540*** (0.411)	0.038 (0.423)	1.401* (0.778)
Share of tertiary educated workers	1.923** (0.752)	1.784*** (0.262)	1.525*** (0.363)	0.808* (0.475)
Share of workers with permanent jobs	-0.166 (0.445)	-0.352 (0.244)	-0.284 (0.262)	0.453 (0.319)
Share of non-EU workers	0.048 (0.825)	0.655 (0.622)	0.640 (0.481)	-0.301 (0.790)
Share of young workers	0.513 (0.476)	0.244 (0.318)	0.331 (0.303)	-0.303 (0.443)
Value Added per employee (log)	0.410 (0.305)	0.077 (0.190)	0.065 (0.204)	0.220 (0.194)
Number of patents/pop	-160.125 (215.235)	-149.828 (173.361)	-97.334 (170.282)	178.790 (205.676)
Average Share of employees in HT and KIS	0.002 (0.006)	-0.000 (0.004)	0.007 (0.005)	0.001 (0.006)
Average Share of employees in Large firms	-0.211 (1.331)	0.389 (0.287)	0.108 (0.288)	-0.292 (0.359)
Average Share of employees in small firms	-0.544 (1.162)	0.573* (0.338)	-0.656* (0.382)	-1.355* (0.695)
Average Share of tertiary educated workers	-1.684*** (0.559)	-1.118*** (0.258)	-1.201*** (0.373)	-0.684 (0.487)
Average Share of workers with permanent jobs	0.408 (0.782)	0.464* (0.251)	0.418 (0.284)	-0.032 (0.327)
Average Share of non-EU workers	-0.267 (1.017)	-0.435 (0.648)	-0.093 (0.505)	0.332 (0.823)
Average Share of young workers	0.280 (1.252)	0.514 (0.363)	0.588* (0.350)	-0.076 (0.536)
Average Value Added per employee (log)	-0.451 (0.299)	-0.227 (0.189)	-0.194 (0.200)	-0.294 (0.196)
Average Number of patents/pop	647.627 (415.410)	950.137*** (166.221)	684.150*** (214.713)	160.493 (235.158)
Obs	1159	1159	1159	1159
Wald chi2(36)	123.97	161.25	263.67	209.61
Prob > chi2	0.0000	0.0000	0.0000	0.0000
sigma_	1.2961	2.9304	2.7840	0.7609
S.E. (sigma)	0.9326	0.3823	0.3389	0.2035

Note: Clustered robust standard errors in parentheses.

Table 7A. Marginal effects of dynamic random effects probit model with unobserved heterogeneity.  
Dependent variable: High digital skill regions (0/1) – Top 25%

	DSI	Developers	Practitioners	Users
	b/se	b/se	b/se	b/se
High DSI (lag)	0.028 (0.026)			
High DSI (first period)	0.229*** (0.026)			
High DVP (lag)		-0.006 (0.010)		
High DVP (first period)		0.237*** (0.014)		
High PCT (lag)			0.019** (0.010)	
High PCT (first period)			0.185*** (0.012)	
High DSI Use (lag)				0.075*** (0.023)
High DSI Use (first period)				0.213*** (0.026)
Share of employees in HT and KIS	0.002 (0.004)	0.005 (0.004)	-0.001 (0.004)	-0.005 (0.005)
Share of employees in Large firms	0.119 (0.315)	-0.060 (0.260)	0.211 (0.272)	0.413 (0.342)
Share of employees in small firms	0.117 (0.794)	-0.871** (0.376)	0.236 (0.382)	1.458* (0.771)
Share of tertiary educated workers	2.123*** (0.417)	1.665*** (0.272)	1.762*** (0.272)	1.033*** (0.370)
Share of workers with permanent jobs	-0.188 (0.376)	-0.261 (0.288)	-0.515* (0.299)	0.323 (0.340)
Share of non-EU workers	0.006 (0.663)	0.721 (0.556)	0.743* (0.422)	-0.301 (0.758)
Share of young workers	0.817* (0.433)	0.373 (0.336)	0.740** (0.341)	-0.186 (0.437)
Value Added per employee (log)	0.373 (0.340)	-0.016 (0.207)	-0.007 (0.175)	0.388* (0.213)
Number of patents/pop	-109.228 (174.588)	-53.787 (144.739)	-64.521 (180.094)	184.611 (199.656)
<b>ERDF Funds</b>	<b>0.001</b> <b>(0.001)</b>	<b>0.002***</b> <b>(0.000)</b>	<b>0.001*</b> <b>(0.001)</b>	<b>-0.002</b> <b>(0.002)</b>
<b>CF Funds</b>	<b>-0.002</b> <b>(0.003)</b>	<b>-0.005**</b> <b>(0.002)</b>	<b>-0.002</b> <b>(0.002)</b>	<b>-0.002</b> <b>(0.003)</b>
<b>ESF Funds</b>	<b>-0.009</b> (0.006)	<b>-0.002</b> (0.004)	<b>-0.011**</b> (0.006)	<b>0.013***</b> (0.003)
Average Share of employees in HT and KIS	0.006 (0.004)	0.003 (0.004)	0.010** (0.004)	0.003 (0.006)
Average Share of employees in Large firms	0.101 (0.336)	0.160 (0.255)	0.078 (0.291)	-0.247 (0.349)
Average Share of employees in small firms	-0.936 (0.673)	0.127 (0.339)	-1.295*** (0.348)	-1.386** (0.681)
Average Share of tertiary educated workers	-1.881*** (0.438)	-1.208*** (0.270)	-1.333*** (0.264)	-0.840** (0.391)
Average Share of workers with permanent jobs	0.111 (0.430)	0.068 (0.313)	0.178 (0.323)	-0.009 (0.381)
Average Share of non-EU workers	-0.266 (0.686)	-0.655 (0.559)	-0.604 (0.425)	0.260 (0.789)
Average Share of young workers	-0.238 (0.584)	0.156 (0.357)	-0.368 (0.373)	-0.335 (0.581)
Average Value Added per employee (log)	-0.411 (0.345)	0.060 (0.202)	-0.101 (0.164)	-0.386* (0.217)
Average Number of patents/pop	590.906** (230.080)	187400 (164.583)	636.427*** (197.794)	125195 (234.761)



Average ERDF Funds	-0.000 (0.002)	-0.004** (0.002)	-0.001 (0.002)	0.002* (0.001)
Average CF Funds	0.014 (0.009)	0.030*** (0.003)	0.015*** (0.003)	0.014*** (0.005)
Average ESF Funds	-0.014* (0.007)	-0.024*** (0.007)	-0.014*** (0.004)	-0.017*** (0.005)
Observations	1159	1159	1159	1159
Wald chi2(36)	156.55	281.78	431.29	235.32
Prob > chi2	0.0000	0.0000	0.0000	0.0000
sigma_	1.5287	2.9480	2.7023	0.7408
S.E. (sigma)	0.5425	0.4356	0.3812	0.2000

Note: Clustered robust standard errors in parentheses.

## References

- Antonelli C., Colombelli A. (2018), *External and internal knowledge in the knowledge generation function*, in: Antonelli C., *The Evolutionary Complexity of Endogenous Innovation*, 82-108, Elgar
- Antonelli C., Crespi F., Scellato G. (2012). Inside innovation persistence: New evidence from Italian micro-data, *Structural Change and Economic Dynamics*, 23 (4), 341-353
- Balland, P. A., & Boschma, R. (2021). Mapping the potentials of regions in Europe to contribute to new knowledge production in Industry 4.0 technologies. *Regional Studies*, 55(10-11), 1652-1666.
- Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment*, 2008(10), P10008.
- Calvino, F., De Santis, S., Desnoyers-James, I., Formai, S., Goretti, I., Lombardi, S., Manaresi, F. & Perani, G. (2022). Closing the Italian digital gap: The role of skills, intangibles and policies, OECD Report.
- Camagni, R., & Capello, R. (2005). ICTs and territorial competitiveness in the era of internet. *Annals of Regional Science*, 39, 421–438.
- Capello, R., Lenzi, C., & Panzera, E. (2022). The rise of the digital service economy in European regions. *Industry and Innovation*, 1-27.
- Caravella, S., Crespi, F., Guarascio, D., & Tubiana, M. (2021). Heterogeneity in the demand-growth relationship at the firm level: the role of demand sources and innovation/knowledge characteristics. *Economics of Innovation and New Technology*, 30(5), 516-535.
- Castellacci, F., Consoli, D., & Santoalha, A. (2020). The role of e-skills in technological diversification in European regions. *Regional Studies*, 54(8), 1123-1135.
- Celi, G., Ginzburg, A., Guarascio, D., & Simonazzi, A. (2018). *Crisis in the European monetary union*. Oxon: Routledge.

- Celi, G., Guarascio, D., & Simonazzi, A. (2019). Unravelling the roots of the EMU crisis. Structural divides, uneven recoveries and possible ways out. *Intereconomics*, 54(1), 23-30.
- Celi, G., Guarascio, D., & Simonazzi, A. (2020). A fragile and divided European Union meets Covid-19: further disintegration or 'Hamiltonian moment'? *Journal of Industrial and Business Economics*, 47(3), 411-424.
- Cirillo, V., Martinelli, A., Nuvolari, A., Tranchero, M. (2019). Only one way to skin a cat? Heterogeneity and equifinality in European national innovation systems. *Research Policy*, 48(4), 905-922.
- Cirillo, V., Fanti, L., Mina, A., & Ricci, A. (2021). Digitalizing firms: Skills, work organization and the adoption of new enabling technologies (No. 2021/04). LEM Working Paper Series.
- Colnot, L., & Pellegrin, J. (2019). The Contribution of Cohesion Policy to Digitalisation: An Adequate Approach?. Centre for Industrial Studies (CSIL), Milan. Working Paper, (01).
- Crescenzi, R. (2009). Undermining the principle of concentration? European Union regional policy and the socio-economic disadvantage of European regions. *Regional Studies*, 43(1), 111-133.
- Crespi, F., Caravella, S., Menghini, M., & Salvatori, C. (2021). European Technological Sovereignty: An emerging framework for policy strategy. *Intereconomics*, 56(6), 348-354.
- D'Este P., Rentocchini F., Vega Jurado J.M. (2014), The role of human capital in lowering the barriers to engaging in innovation: evidence from the Spanish innovation survey, *Industry and Innovation* 21 (1), 1-19
- Dosi, G., Nelson, R. R., Winter, S. G., & Winter, S. G. (Eds.). (2000). The nature and dynamics of organizational capabilities. Oxford university press.
- Dosi, G., & Marengo, L. (2015). The dynamics of organizational structures and performances under diverging distributions of knowledge and different power structures. *Journal of Institutional Economics*, 11(3), 535-559.
- Fanti, L., Guarascio, D., & Tubiana, M. (2021). Skill mismatch and the dynamics of Italian companies' productivity. *Applied Economics*, 53(59), 6790-6803.

- Fusillo F., Consoli D., Quatraro F. (2022) Resilience, Skill Endowment, and Diversity: Evidence from US Metropolitan Areas, *Economic Geography* 98 (2), 170-196
- Gareis, K., Birov, S., & Husing, T. (2014). E-skills for jobs in Europe – Measuring progress and moving ahead (Final EU Report). Retrieved from <http://ec.europa.eu/DocsRoom/documents/4398/attachments/1/translations/en/renditions/pdf>
- Gräbner, C., & Hafele, J. (2020). The emergence of core-periphery structures in the European Union: A complexity perspective (No. 6). ZOE Discussion Papers.
- Gräbner, C., Heimberger, P., Kapeller, J., & Schütz, B. (2020). Is the Eurozone disintegrating? Macroeconomic divergence, structural polarisation, trade and fragility. *Cambridge Journal of Economics*, 44(3), 647-669.
- Falck, O., Heimisch-Roecker, A., & Wiederhold, S. (2021). Returns to ICT skills. *Research Policy*, 50(7), 104064.
- Fernandes, C., Farinha, L., Ferreira, J. J., Asheim, B., & Rutten, R. (2021). Regional innovation systems: what can we learn from 25 years of scientific achievements? *Regional studies*, 55(3), 377-389.
- Helsper, E. J., & Van Deursen, A. J. A. M. (2015). Digital skills in Europe: Research and policy. Digital divides: The new challenges and opportunities of e-inclusion, 195, 125.
- Hidalgo, A., Gabaly, S., Morales-Alonso, G., & Urueña, A. (2020). The digital divide in light of sustainable development: An approach through advanced machine learning techniques. *Technological Forecasting and Social Change*, 150(2019), 119754. <https://doi.org/10.1016/j.techfore.2019.119754>
- Kleinknecht, A. (2020). The (negative) impact of supply-side labour market reforms on productivity: an overview of the evidence. *Cambridge Journal of Economics*, 44(2), 445-464.
- Maynou, L., Saez, M., Kyriacou, A., & Bacaria, J. (2016). The impact of structural and cohesion funds on Eurozone convergence, 1990–2010. *Regional Studies*, 50(7), 1127-1139.

- Montresor, S., Orsatti G., Quatraro F. (2022), Technological novelty and key enabling technologies: evidence from European regions, *Economics of Innovation and New Technology*, 1-22
- Müller, J. M., Buliga, O., & Voigt, K. I. (2021). The role of absorptive capacity and innovation strategy in the design of industry 4.0 business Models-A comparison between SMEs and large enterprises. *European Management Journal*, 39(3), 333-343.
- OECD (2001). Understanding the digital divide (Vol. 49, Issue 4). <https://doi.org/10.1787/236405667766>
- Pérez-Morote, R., Pontones-Rosa, C., & Núñez-Chicharro, M. (2020). The effects of e-government evaluation, trust and the digital divide in the levels of e-government use in European countries. *Technological Forecasting and Social Change*, 154(February), 119973. <https://doi.org/10.1016/j.techfore.2020.119973>
- Psycharis, Y., Tselios, V., & Pantazis, P. (2020). The contribution of Cohesion Funds and nationally funded public investment to regional growth: Evidence from Greece. *Regional Studies*, 54(1), 95-105.
- Reljic, J., Evangelista, R., & Pianta, M. (2021). Digital technologies, employment and skills. *Industrial and Corporate Change*, Online first, <https://doi.org/10.1093/icc/dtab059>.
- Reveiu, A., Vasilescu, M. D., & Banica, A. (2022). Digital divide across the European Union and labour market resilience. *Regional Studies*, 1-15.
- Rückert, D., Veugelers, R., & Weiss, C. (2020). The growing digital divide in Europe and the United States (No. 2020/07). EIB Working Papers.
- Santoalha, A., Consoli, D., & Castellacci, F. (2021). Digital skills, relatedness and green diversification: A study of European regions. *Research Policy*, 50(9), 104340.
- Thonipara, A., Sternberg, R. G., Proeger, T., & Haefner, L. (2020). Assessing the Digital Divide and its Regional Determinants: Evidence from a Web-Scraping Analysis (No. 25/2020). ifh Working Paper.

Van Dijk, J. A. G. M. (2008). *The digital divide in Europe*. The handbook of Internet politics.

Zillien, N., & Marr, M. (2013). *The digital divide in Europe*. In *The digital divide* (pp. 75-86). Routledge.