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place-based **innovation** of **cultural and creative** industries in **non-urban** areas

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Executive Summary

The COVID-19 pandemic crisis has affected all sectors of the economy globally, and hence has been a major shock for creative and cultural activities in non-urban regions too. Creative and cultural activities particularly suffered from the shutdown of events and gatherings when lockdown measures were put in place. At the same time, innovation enabled by a combination of creativity and digital technologies led to all kinds of solutions to move creative and cultural activities to the digital space. The ability to do so depended on the skills and capabilities already available to allow the digital transformation of creative and cultural activities. The intuition is that regions with stronger creative and digital skills and capabilities also showed higher socio-economic resilience.

Against this backdrop, this report (related to Task 1.5) aims to shed light on the role of digital technologies and the occupational composition of the region in shaping the ability of creative and cultural activities to resist the COVID-19 shock. Building on the data collected and organised in the context of previous tasks in Work Package 1, we compare and descriptively assess regions before and after the COVID-19 shock. In particular, we identify classes of occupations and trademarks that rely on digital technologies and assess whether occupations and trademarks that are more digital tend to better withstand the COVID-19 shock across urban and non-urban regions. Besides, building on the evolutionary approach that we also used in Deliverable 1.2 "New domains in CCIs in non-urban regions" (including Tasks 1.3 and 1.4), we explore possible paths for recovery based on our measures of relatedness and relatedness density.

Our analysis highlights four main findings on the relationship between creative and cultural activities and digital skills and capabilities in non-urban regions.

First, based on our descriptive evidence, we show that, on average, the shares of digital and creative and cultural occupations (CCOs) have not changed much over the time period considered (2018 to 2021). Instead, analysing the distribution of trademarks reveals an overall increment in the share of digital trademarks in the years of the pandemic, with the increase being more pronounced in non-urban regions. This trend suggests that non-urban regions developed more digital goods and services than urban regions.

Second, we show how occupations and trademarks which are "more digital" weathered better the COVID-19 shock. For instance, when comparing the share of jobs in the regions in the period before and during the pandemic by the intensity of digital skills, we find that the number of regions experiencing a growth in employment in the occupation group compared to regions experiencing a decline in employment in the occupation group is higher in the case of high digital skills occupations, while the opposite holds (more regions experiencing employment contractions) for non-digital skills. We interpret this finding as suggestive of a possible role of digital skills in dampening the shock and making regions more resilient.

As an alternative approach to studying resilience, we computed a sensitivity index through which we wanted to capture the sensitivity of a region to the COVID-19 shock and, which connects to our third point. The maps reveal that the presence of occupations with high and medium digital skills had a more positive influence on the resilience of the regions than the presence of occupations with low and non-digital skills in the EU regions. Interestingly, when looking at the map with the sensitivity of creative occupations, the variation occurs mostly between countries, suggesting a possible role for national-level interventions in influencing the impact of COVID-19 on CCOs.

Lastly, our analysis of the occupation space for non-urban regions indicates that high digital skills intensity occupations may not be leveraged towards diversification – as they are not central in the network. A better choice may be occupations with medium digital skills intensity and even some CCOs, given their relatively central position and connection to resilient medium and high digital skill occupations. Overall, however, the comparison with urban regions suggests more densely populated and urbanised areas are in a better position to leverage digital occupations and CCOs.

Overall, our findings provide an original perspective to understand the socio-economic resilience of creative and cultural activities during the pandemic and in particular the specific patterns for non-urban regions. Our analysis is complementary to quantitative studies using more standard economic data, but also to qualitative studies of the solutions enacted by specific creative industries or specific regions. The findings can inform policymakers and spur further research leveraging an evolutionary perspective.

1. Introduction

In order to understand and evaluate the dynamics of regional development, it is crucial to not only look at how a region fares during times of economic expansion or overall macroeconomic stability but also to investigate its resilience in times of economic contraction and economic instability. Paying attention to the ability of a regional economy to cope with unexpected events is of paramount importance also for policymakers, whose interventions and policies can greatly contribute to the ability of a region to resist and recover from shocks (North, 2005).

In this respect, recent technological advances in digital technologies – along with making our world more interconnected and thus exposing the world as a system to shock propagation – create new opportunities for fostering resilience. The recent experience of the COVID-19 pandemic provides a clear example. The presence of suitable information and technology infrastructure and the ability to leverage digital technologies was paramount during lockdown and social distancing, in which a large part of the workforce had to work remotely (Oikonomou *et al.,* 2023). In addition, digital technologies were also key in maintaining consumption levels by shifting to digital platforms, both in terms of goods (Alipour *et al.,* 2022) and arts and culture (Noehrer *et al.,* 2021).

These considerations are particularly relevant and interesting in the context of the differences between urban and non-urban regions and concerning cultural and creative activities. Regarding the divide between urban and non-urban areas, researchers have shown that non-urban regions tend to be more specialised and rely more heavily on relatively few industries or economic activities (Diemer *et al.,* 2022; Pinheiro *et al.,* 2022; Rodríguez-Pose, 2018). Building on these arguments, non-urban regions are likely to perform overall less well in terms of resilience and thus be more strongly affected by shocks and disturbances. This may be especially true when considering high-tech industries, as knowledge- and technology-intensive occupations tend to be concentrated in more urbanised areas (Tessarin *et al.,* 2023a, 2023b). With respect to cultural and creative activities, these industries were, in general, among the most affected by the recent lockdowns and social distancing measures (Jeannotte, 2021; Noehrer *et al.,* 2021). Once again, however, some evidence suggests that creative and cultural activities that could not rely on strong digital skills and high-quality internet access – both likely to be challenges in non-urban regions – were likely among the most affected (Brooks and Patel, 2022).

Against this backdrop, this report focuses on Task 1.5 of the IN SITU project. More specifically, in the analysis presented here, we aim to shed some light on the role of digital technologies and the occupational composition of the region in shaping the ability of creative and cultural activities to resist the COVID-19 shock. Building on the data collected and organised in the context of the previous tasks, we compare and descriptively assess regions before and after the COVID-19 shock. In particular, we identify classes of occupations and trademarks that rely on digital technologies and assess whether occupations and trademarks that are more digital tend to better withstand the COVID-19 shock across urban and non-urban regions. Besides, building on the evolutionary approach we also used in the Deliverable 1.2 “New domains in CCIs in non-urban regions” (including Tasks 1.3 and 1.4), we explore possible paths for recovery based on our measures of relatedness and relatedness density.

To fulfil the objective of this report, we opt for an original quantitative approach based on data on occupations and trademarks, inspired by our previous contributions within the IN SITU project. Other approaches, including quantitative and qualitative methods focusing on the resilience capacity of workers and the cultural and creative sector and covering topics such as working conditions, impacts on the informal economy, and the scope and effectiveness of relief measures for a class of intermittent workers, are valid alternatives and can offer complementary evidence. Although these topics are not being addressed in this report, themes linked to social resilience and the recovery capacity of the cultural and creative sector will be handled by other Work Packages in the IN SITU project.

This report is organised in the following way. Section 2 provides a theoretical review of key points, covering the topics of resilience (2.1), cultural and creative activities during the pandemic (2.2), and digital skills (2.3) and relatedness (2.4) as means for resistance to exogenous shocks. In Section 3 we present the methodological procedures, including data sources and methods, paying particular attention to the classification of occupations and trademarks into digital ones, and identifying the classes of occupations and trademarks most pertinent to digital technologies. The results of our analyses are reported in Section 4, showing the resistance to the COVID-19 shock of different occupations across levels of our digital classification and urban and non-urban types of regions. Leveraging the evolutionary approach presented in Deliverable 1.2, we analyse their position in the occupation space and provide some insights on the possible role of digital occupations in recovering from the COVID-19 shock. To close the report, Section 5 provides some final remarks. Appendices A, B, and C present detailed data tables developed in this research.

2. Conceptual framework

2.1. Resilience

Regional economic resilience has gained prominence within regional studies, particularly after the 2008 global financial crisis and, most recently, after the COVID-19 pandemic, drawing increased attention to the resilience of urban and regional economies. This literature usually assesses three types of resilience based on engineering (bounce back), ecological (ability to absorb), and evolutionary (positive adaptability) (Martin, 2012; Martin and Sunley, 2015). The evolutionary perspective has emerged as a dominant lens in studying regional economic resilience, emphasising resilience as a continual process of self-organisation rather than a return to a stable equilibrium (Bristow and Healy, 2014).

The evolutionary economic geography (EEG) theory stresses the dynamic evolution and structural changes in an economy based on its previous capabilities and resources (Boschma, 2015; Kogler *et al.,* 2023; Simmie and Martin, 2010). In this context, the seminal work of Martin (2012) introduces the conceptual framework of regional economic resilience, citing four dimensions: resistance, recovery, re-orientation, and renewal. Resistance symbolises the degree of sensitivity or the initial impact of shocks; recovery indicates the speed and degree of recovery from shocks; re-orientation refers to the extent and adaptability of a regional economy in response to the shock; and finally, renewal indicates the extent to which a region renews its pre-shock growth trajectory or changes to a new trajectory (Martin, 2012). This conceptualisation underscores the importance of adaptation and adaptability, emphasising the region's ability to withstand shocks and forge new growth paths. Boschma (2015) defined regional economic resilience in terms of adaptation and adaptability. The first refers to the path dependence process, and the latter is about creating new paths. In this sense, resilience does not just refer to the regional ability to accommodate shocks but also to their long-term adaptability, which is the ability of regions to develop new growth paths (Boschma, 2015).

Numerous empirical studies have adhered to the EEG theory, probing into the drivers of regional economic resilience (Cortinovis, 2012; Di Pietro *et al.,* 2021; Fritsch and Kublina, 2018; Grabner and Modica, 2022; Hu *et al.,* 2022; Martin *et al.,* 2016; Martin and Sunley, 2015; Sedita *et al.,* 2017), with a particular focus on economic structure (such as number of firms, entry of new firms, employment growth, among others). Industrial and business structures are among the crucial regional subsystems investigating how diverse or specialised economies respond to shocks and how different degrees of sectoral interrelatedness impact regional responses. Another front of studies evaluates the innovation capacity as a critical driver of regional economic resilience (Balland *et al.,* 2015; Filippetti *et al.,* 2020; Martin and Sunley, 2020; Rocchetta *et al.,* 2022; Tóth *et al.,* 2022; van Meeteren *et al.,* 2022). For those authors, innovation helps regions adapt to changes and promote long-term re-orientation and renewal. Interestingly, some authors also suggest that the exposure to the shock itself may contribute to technological development and innovation (Steijn *et al.,* 2023).

However, the specific nature of a shock influences the resilience process. The COVID-19 pandemic has brought significant losses for countless businesses, leading to severe disruptions for many industries (Khlystova *et al.,* 2022; OECD, 2020). Strict measures, such as social distancing, quarantines and lockdowns, were widely adopted to prevent the virus from spreading, influencing every single industry of the economy. Countries introduced many support measures, such as job retention schemes, one-off grants and funding to leverage the long-term economic and social impacts of the COVID-19 pandemic (Morceiro *et al.,* 2022; OECD, 2020). However, industries, regions and workers were impacted in some way at different times in all corners.

Understanding the determinants of regional economic resilience in the context of COVID-19 requires a nuanced approach. Factors beyond industrial structures, such as the characteristics of the regions, local capabilities, skills of workers and digital capacity, need to be further investigated in a joint vision. Based on these theoretical elements, scholars need to analyse the continuous adaptation process (Pike *et al.,* 2010) to understand how regions suffer and survive the various shocks and disturbances they are subject to and then understand the determinants of regional resilience.

2.2. Relatedness and regional adaptability

Relatedness has become a key input to outline possibilities for technological and economic re-combination and diversification. There is a consensus within the EEG literature that the probability of firms, regions and countries entering new activities is a function of the number of related activities in which they are already specialised (Boschma et al., 2015; Hidalgo et al., 2018; Juhász et al., 2021).

The relatedness concept captures the necessary capabilities that reside in a region for developing new activities. From an occupational perspective, the relatedness between occupations can be either complementary or similar (Farinha *et al.,* 2019; Galetti *et al.,* 2022; Neffke, 2019). Similarity indicates that two occupations might require similar sets of skills, while complementarity indicates that the skill sets of two occupations are complementary in fulfilling certain tasks (Farinha *et al.,* 2019).

Scholars have been applying occupation data to study the diversification of regions in various countries. For example, on U.S. cities (Muneepeerakul *et al.,* 2013; Farinha *et al.,* 2019), on Norwegian regions (Fitjar and Timmermans, 2017), on Brazilian regions (Galetti *et al.,* 2021, 2022), and on European regions (Tessarin *et al.,* 2023c). These studies confirmed the importance of relatedness to influence the entry of new occupations in a region.

However, the relatedness between occupations might not be static (Acemoglu and Restrepo, 2019) and varies among regions based on their local market structure (Tessarin *et al.*, 2023c). From this perspective, tracing the skill set of occupations and regions over time is important for understanding the impact of new technologies and digitalisation in order to visualise the potential opportunities for regions to adapt and reinvent themselves (Tessarin *et al.*, 2023c).

2.3. Cultural and creative activities during the pandemic

The COVID-19 pandemic has changed the way social capital is created and replicated. It significantly restricted the traditional forms of networking between creative workers and communities, altering demand and consumption patterns and creating the demand for new business models (Khlystova *et al.,* 2022; UNESCO, 2021).

The recent events of the COVID-19 pandemic have demonstrated that the cultural and creative industries adopted new business models to operate during this crisis (Brooks and Patel, 2022; Jeannotte, 2021; Noehrer *et al.,* 2021). On one hand, some museums started to offer online exhibitions, while musicians delivered concerts via online streams or recorded their performances (Agostino *et al.,* 2020), changing the customers' experience, demand and consumption. On the other hand, the literature has also demonstrated that most small businesses, freelancers and self-employed people in the creative industries struggled to adapt to new changes and be resilient during the pandemic (UNESCO, 2021).

Undertaking a systematic review of the recent relevant literature, Khlystova *et al.* (2022) provides some insights into the effects of the COVID-19 pandemic on the cultural and creative industries. They conclude that, with a few exceptions, the creative industries have not shown – or was not able to exhibit – sufficient resilience to the recent crisis. Overall, extant studies (Brooks and Patel, 2022; Jeannotte, 2021) suggest that the pandemic brought to the forefront inherent vulnerabilities linked to the precarity and informality of the cultural and creative sector, calling for a longer-term recovery and growth strategy to effectively meet social and economic challenges ahead and beyond the COVID-19 pandemic (OECD, 2020; UNESCO, 2021).

The loss of business opportunities in the cultural and creative sector also meant a loss of income for non-standard workers, such as artists and freelancers, since they depend on their personal business networks to find opportunities (events, fairs and festivals, for example) (Voldere *et al.*, 2020). In this respect, it is important to keep in mind that, in addition to reinforcing the unstable income flow of these cultural and creative workers, their working conditions were already precarious before the COVID-19 crisis.

However, other studies suggest that regions dominated by the creative industries can demonstrate resilience to external shocks by producing creative goods and services based on the input-output relationships with other sectors within a region, facilitating more diversification (Boschma, 2015; Khlystova *et al.,* 2022; OECD, 2020).

As an important component of the knowledge economy, the cultural and creative industries can be characterised as entrepreneurial, innovative, sustainable and flexible. Such industries are recognised as particularly resilient to external crises (Herbane, 2019), and their flexibility is the cornerstone in explaining it (Felton *et al.,* 2010).

One of the demonstrations of such flexibility was seen during periods of lockdown when creative workers and support industries found new opportunities to stay active and attractive within the cultural industries (Noehrer *et al.,* 2021). For instance, many cultural service providers transferred content online, often for free. In this way, they managed to keep the audience engaged and satisfy the sharp increase in demand for cultural content due to physical restrictions (Agostino *et al.,* 2020; Khlystova and Kalyuzhnova, 2023). Although permanent online events or free offerings are not viable in the long term, they have opened the door to many innovations and new markets.

2.4. Digital skills and markets to overcome crises

The COVID-19 pandemic has pushed many businesses, including within the cultural and creative industries, to develop new and more resilient ways of operating rapidly (Khlystova *et al.,* 2022; UNESCO, 2021; Steijn *et al.*, 2023; Oikonomou *et al.*, 2023). Certainly, there are also many cases in which workers have moved on to other occupations outside the cultural and creative sector, still feeling personal losses from the pandemic period and the loss of their jobs (Voldere *et al.*, 2020). In this report, we will cover the impact on jobs that can be measured by the Labour Force Survey (LFS) data.

In order for businesses and organisations to survive in times of crisis, incorporating and adapting to the digital world was one of the solutions sought by many during the pandemic. Mainly due to lockdown measures and movement restrictions, several companies began offering goods and services on digital platforms (UNESCO, 2021; Voldere *et al.*, 2020). Sectors producing information and communication technologies also changed their service offerings to quickly respond to new structures of social interaction based on online or remote work. In turn, workers also needed to quickly readapt and perform their tasks using new equipment and technologies, and many had to learn to perform their functions in completely different ways than they were used to (Cortes and Forsythe, 2023; Tessarin and Morceiro, 2022). For instance, artists and creators now produce content like books, visual arts and music at lower costs and have access to new distribution channels through online streaming (Khlystova *et al.*, 2022; Voldere *et al.*, 2020), while museums and galleries have been digitising their collections and providing consumers with virtual tours (Cortes and Forsythe, 2023).

In this sense, the impact of the pandemic was felt differently by different workers. In addition to the waves of the pandemic affecting regions with different intensities and temporal scopes, some occupations were better able than others to adjust to all the unexpected transformations (Cortes and Forsythe, 2023; Fana *et al.,* 2020). Therefore, the intensity of the pandemic's impact on the regions – considering the labour market and the productive structure – was uneven.

There are also differences in the cultural and creative sectors. The radio and television broadcasting sector saw a sharp increase in audiences, while music and artistic performance suffered from cancelling concerts and festivals (Voldere *et al*., 2020). The disruption of physical distribution, replaced by online platforms or online presentations, has also had a major impact on business networking opportunities for workers in the cultural and creative sectors. The cancellation of events, especially for artists and freelancers, has drastically disrupted the cultivation of professional networks, which guarantee the future viability of their businesses (Voldere *et al*., 2020).

In addition, it is important to keep in mind that the cultural and creative industries are made up of a large number of freelancers and temporary and intermittent workers (UNESCO, 2021; Voldere *et al*., 2020). Many small businesses rely on these non-standard workers to carry out their activities.

However, this type of worker is often not fully captured in structural surveys[1] and, therefore, requires a specific approach to be included in structural questionnaires.

Digital skills are important for users of ICTs (Oikonomou *et al.,* 2023), enabling access to external advanced knowledge and information, but also for workers in sectors closer to the production of ICTs, for application to upgrade existing industrial activities. The adaptation to a massive digitalisation coupled with emerging technologies (such as virtual and augmented realities) has the potential to create new forms of work organisation and business models with market potential.

According to CEDEFOP (2021), digital skills function as a driver of digital transitions. Apart from particular sectors and occupations (e.g., ICT technicians and ICT professionals) that develop and provide digital goods and services, these skills are increasingly becoming a transversal requirement in most occupations and sectors. The COVID-19 pandemic and its wide-ranging implications have accelerated the demand for digital skills in many occupations, especially non-ICT ones (CEDEFOP, 2021). Effective use of digital skills has proven to be a driver of resilience, helping workers and entire organisations adapt to the new realities shaped by the pandemic, especially in creative and cultural domains (Brooks and Patel, 2022).

In some occupations and economic sectors – such as food and accommodation, wholesale and retail trade, or arts and recreation – digitalisation and remote work were less straightforward options (CEDEFOP, 2021; Noehrer *et al.*, 2021). However, digital transformation in these sectors also moves toward safer workplaces and new market experiences.

According to the arguments of EEG, existing competencies and capabilities accumulated in a given territory can be very useful in shaping the possibilities for a region to be resilient. In this context, developing digital skills is an important part of building resilience to economic and social shocks. Such digital skills range from the knowledge to broadcast online, reach and interact with customers virtually, digitise documents and images, and make them available to a wide audience, to knowledge to work on remote platforms, carrying out process automation tasks and programming language. Digital skills can complement the capabilities already present in regions, making them more capable and resilient to adverse shocks.

[1] Some situations that exemplify these cases: freelancers who have two jobs may indicate that their main source of income is outside the cultural and creative sector; or intermittent workers may not be employed at the time the survey is collected or also have a secondary income source.

3. Data and methodology

The objective of this report (Deliverable 1.3) is to offer an analysis of the socioeconomic resilience of the cultural and creative industries during the COVID-19 pandemic, from an evolutionary perspective on regional resilience (Boschma, 2015), stressing how regional capabilities to innovate and adapt are most relevant for resilience (Filippetti *et al.,* 2020) and acknowledging the key role played by digital skills in allowing all organisations, including cultural and creative sectors, to switch to modes of service provision not requiring physical proximity during the pandemic. In this task, we compare non-urban and urban regions in terms of their related knowledge space and the capabilities related to digital occupations and digital product or market development. To do this, we zoom into the period just before and during the pandemic (2018 to 2021). Below we explain the procedures and data used in this task.

3.1. Data sources

We combined information about urban and non-urban regions on occupations and trademarks from different databases to study digital-skills occupations and digital trademark classes. As part of continuous work, part of the methodology used in this report was prepared previously for IN SITU Deliverable 1.1 "Socioeconomic contributions and spillovers of CCIs in non-urban regions" (Tessarin *et al.*, 2023b) and Deliverable 1.2 "New domains in CCIs in non-urban regions" (Tessarin *et al.*, 2023a). In the following sections, we revisit these central concepts and introduce new ones.

3.1.1. Occupation data

Data on occupations comes from the Labour Force Survey (LFS), Eurostat, a national household survey conducted by European countries to produce official national statistics following the same statistical regulation. This database collects information on individuals indicating occupation and place of work, among many other variables.

We had access to the LFS microdata in the scope of the IN SITU project, so we could leverage disaggregated information from occupations and NUTS regions to conduct this study. This set of LFS microdata provides occupation information at the 3-digit level at ISCO-08 (available from 2011 onwards), which covers 130 exclusive codes and regional desegregation by NUTS level 2.

We cleaned the database, removing information without comparable codes for ISCO and workers without occupational or regional identification. We also dropped workers from regions outside European Union countries, as they are out of scope for our report. In the end, proportionally to the total, little information was lost in the process of cleaning and organising data. After this process, we dropped only 4% of the workers.

In total, our dataset covers 18.6 million workers between the period 2011 to 2021, about 1.7 million workers per year.

As LFS is a national household sample survey conducted by European countries, verifying whether the regional distribution of employment is similar to that reported by the Eurostat statistics based on administrative records is essential. Tessarin *et al.* (2023a) worked on verifying LFS regional employment distribution to see whether the national surveys are well-balanced and represent the large and small regions well. They found a high Pearson correlation index between a country's regional employment distribution based on the LFS and the Eurostat regional employment, above 90% for most EU countries. Therefore, their exercise ensures the validity of data from LFS at the subnational level.

3.1.2. Trademarks

Trademark data comes from the European Union Intellectual Property Office – EUIPO Trademark database, and we accessed from the ISI-Trademark Data Collection (ISI-TM).[2] It provides detailed information on trademarks filed at the EUIPO and the USPTO (Neuhäusler *et al.,* 2021).

We selected the EUIPO trademark applications filed by applicants with addresses in one of the European regions. We excluded filings from Andorra as there is no information for this region in the other database. We also excluded incomplete occurrences, for instance, when there was no "applicant_ID", because it is impossible to allocate a region in this case. After cleaning and processing the data, we dropped 5.5% of the dataset due to missing information.

Notice that the EUIPO filings differ from trademarks filed at national trademark offices: these are not easily available for all countries. Flikkema, De Man and Castaldi (2014) found that trademarks filed at the EUIPO were more likely to refer to innovation than national trademark filings. In this sense, our focus on EUIPO filings makes the trademark-based innovation metrics more valid than metrics based on national filings.

3.1.3. Data period

In this report, we aim to analyse the impacts of the COVID-19 pandemic on regions. To do so, we need to compare the pre-pandemic period with the years of the pandemic.[3] We started the analysis in 2014

[2] We are especially grateful to Peter Neuhäusler, from Fraunhofer Institute for Systems and Innovation Research (ISI), for his help in making the geocoded dataset available.

[3] Our database only includes data up to 2021. As the first year that may be considered post-pandemic is 2023, we can only compare years before and during the pandemic.

to maintain a balanced sample of regions – although data has been available since 2011 in ISCO-08 – as between 2011 and 2013, some countries made adjustments to their regional division, and there were no data for all regions. As for the period of the pandemic, we are considering the years 2020 and 2021, given that there is still no data available to analyse subsequent years.

3.1.4. NUTS regions

As we are working with two different databases, we had to choose a regional level of analysis that would fit the data availability across them, especially one that would allow us to classify them by the degree of urbanisation.

The LFS provides information for 32 European countries in 1- and 2-digit NUTS regions. We are working with the most disaggregated version at the 2-digit NUTS level. However, Bulgaria, Malta and Slovenia do not have the granularity of data by profession necessary to carry out our research, so these three countries were excluded. In turn, the Netherlands does not provide NUTS 2 disaggregation, so we had to compile the entire country as if it were just one region to keep it in the analysis. Finally, the United Kingdom was not included as Eurostat does not provide data for this country after 2019.

As for trademarks, EUIPO provides information at the NUTS 3 level. Therefore, we had to consolidate them into the NUTS 2 level to create a dataset matching the same analysis level as occupations.

We also made a concordance table between NUTS 2 region codes with all their variations (in names or codes) and changes over the years. Sometimes, the European Commission amends the classification if a country requires changing the regional breakdown. For instance, from NUTS 2016 to NUTS 2021, at the NUTS level 2, several regions had names changed in Spain; Hungary had one region discontinued and three new ones created; Norway had seven regions rearranged into six, one had been through a large revamp, and a new one was created. In 2011, the NUTS 1 code of Greece was changed from GR to EL, consequently changing the codes of all NUTS 2 and 3 levels; in addition, another four regions were reclassified. These and all other amendments over the analysed period were included in the concordance table so we do not miss data from the restructured regions.

3.1.5. Non-urban and urban regions

The division of regions by degree of urbanisation is based on the classification developed by Eurostat to provide standardised territorial typologies for all the countries of the European Union. The methodology classifies Local Administrative Units (LAU) based on a combination of criteria of geographical contiguity and minimum population in an area (Eurostat, 2021). As a result, the areas are assigned to three degrees of urbanisation:

1. **Cities** (densely populated areas): where at least 50% of the population lives in urban centres – urban centres have a population density of at least 1,500 inhabitants per km² and collectively a minimum population of 50,000 inhabitants.

2. **Suburbs** (intermediate density areas): where at least 50% of the population lives in urban clusters and less than 50% lives in urban centres – urban cluster means areas with a population density of at least 300 inhabitants per km² and a minimum population of 5,000 inhabitants.
3. **Rural** (thinly populated areas): where at least 50% of the population lives in rural areas – it covers all other areas not identified as urban centres or as urban clusters.

This territorial typology is only available for NUTS 3 regions, and there is no typology at NUTS 2 digits. However, the LFS occupation data used in this work covers regions at NUTS level 2. Therefore, it was necessary to aggregate the NUTS 3 areas to the NUTS 2 regional level to perform this work.

In the 'History of NUTS' file[4], the 3-digit NUTS regions are classified as predominantly urban, intermediate and rural. We use the distribution of employed persons in each NUTS 3 to classify NUTS 2 regions. In the end, we have two groups:

1. **Urban:** a region is predominantly urban when the majority proportion of employed people work in an area classified as urban;
2. **Non-urban:** comprises the regions in which the proportion of non-urban jobs is greater than 50%.

In total, there are 294 regions in the European Union. Note that for the analysis of trademarks, all regions have been included; in the case of occupations, regions of three countries have been excluded (Bulgaria, Malta, and Slovenia) due to the absence of ISCO 3-digit occupation data; and The Netherlands was classified entirely as an urban region. Appendix A presents the number of urban and non-urban regions by country according to this methodology.

One of the concerns about this regional reclassification exercise is that it may be capturing large urban agglomerations consistent with the identification of global cities as urban regions and everything else as non-urban. However, given the unavailability of NUTS 3 data for the analysis, we believe this may be the best that can be achieved now.

[4] Available here: https://ec.europa.eu/eurostat/web/nuts/history

3.2. Methods to map digital and creative activities

3.2.1. Cultural and creative occupations (CCOs)

Several studies within economic geography and geography of innovation have used industry-based definitions of creative and cultural activities to measure their role in regional development (Innocenti and Lazzeretti, 2019; Lee, 2020; Lee and Drever, 2013; Protogerou *et al.,* 2017; Stam *et al.,* 2008).

More recently, we have seen a shift from defining creative and cultural activities based on industrial classifications towards defining them based on occupations. The key advantage of using occupations is that one can map the contribution of these activities across the whole economy. Many creative workers are not employed in creative industries but rather in industries that complement occupations based on other skills and talent (Cruz and Teixeira, 2012).

By now, many studies have adopted the occupation-based approach (Bakhshi *et al.,* 2013; Boschma and Fritsch, 2009; Markusen *et al.,* 2008; OECD, 2022a; Rodríguez-Pose and Lee, 2020; Tessarin *et al.,* 2023a, 2023b). In this case, the emphasis is more on what workers do than where they work (Feser, 2003; Markusen *et al.,* 2008).

Overall, it has become evident that occupation-based definitions allow better capturing of the actual contribution of creative and cultural activities, while industry-based definitions tend to grossly underestimate it (Eurostat, 2018; OECD, 2022b). We follow these insights and leverage the occupation-based perspective in this report.

In line with this literature[5], we have selected a typology to identify occupations broadly considered cultural and creative. Table 1 presents the occupations classified by national statistical offices and compiled by Eurostat for standardisation purposes as fully related to cultural and creative occupations.

[5] For more arguments on the limitations and benefits of using occupations to classify cultural and creative activities, see the previous IN SITU report, D1.2 - "New domains in CCIs in non-urban regions" (Tessarin *et al.*, 2023a) available on the IN SITU website.

Table 1 - Description of cultural and creative occupations (ISCO-08 at 3 digits)

ISCO-08	Cultural and creative occupations
216	Architects, planners, surveyors and designers
235	Other teaching professionals
262	Librarians, archivists and curators
264	Authors, journalists and linguists
265	Creative and performing artists
343	Artistic, cultural and culinary associate professionals
352	Telecommunications and broadcasting technicians
441	Other clerical support workers
731	Handcraft workers

Source: Authors, based on Eurostat.

Because the LFS microdata is only available at ISCO-08 at the 3-digit level, we had to consider all occupations within the 3-digit level. Due to the scarcity of data on the 4-digit level, most studies follow the same strategy (Eurostat, 2018; OECD, 2022a) and adopt the complete composition of 3-digit ISCO codes to compute cultural and creative occupations.[6]

For this report, cultural and creative workers are defined as all individuals working under these ISCO-08 codes regardless of which industry the worker is allocated – inside or outside cultural and creative industries.

3.2.2. Digital occupations

Each occupation comprises a singular set of skills, and the number of skills varies per occupation. It depends on the requirements and tasks related to each occupation. For example, one occupation could involve more manual and dexterity skills; others demand more social skills; while others demand more cognitive skills to solve complex tasks.

The European Commission produces the European Skills, Competences, Qualifications and Occupations (ESCO) in the European Union context. This classification identifies and categorises skills and competences and links them to occupations, describing systematically the skills needed to be

[6] In the report D1.1 – "Socioeconomic contributions and spillovers of CCIs in non-urban regions" (Tessarin *et al.,* 2023b) we show which occupations were classified as CCOs at ISCO-08 at 3 and 4 digits level.

performed in an occupation. In total, the ESCO list comprises 13,896 skill types (European Commission, 2022).

In 2022, the European Commission proposed a methodology to label ESCO digital skills and knowledge concepts, combining human labelling and validation with machine learning algorithms (European Commission, 2022). According to this methodology, the digital skills and knowledge concepts involve “the confident, critical and responsible use of, and engagement with, digital technologies for learning, at work, and for participation in society. It includes information and data literacy, communication and collaboration, media literacy, digital content creation (including programming), safety (including digital well-being and competencies related to cybersecurity), intellectual property related questions, problem-solving and critical thinking” (European Commission, 2022, p. 15).

From this recent effort, connecting the ISCO (International Standard Classification of Occupations) categories with a list of ESCO digital skills and competencies is now possible.

To fulfil the objective of this report and assess digital skills, we relied on this list and followed a few steps to adapt it to the information available in the LFS. The first step was to group the ESCO files to relate ISCO codes to the identifier of each skill. The second step was to filter only ‘digital skills’, excluding ‘digital knowledge’. This was necessary to achieve a more specific variable, given that knowledge includes quite broad definitions. European Commission (2022) explains that there is a risk of inflating the list of digital skills when adding concepts with no immediate connection with the digital domain. We followed this argument and excluded digital knowledge since many of them include the name of a digital tool or software required to perform a task. In the third step, we only keep ‘essential skills’ and exclude ‘optional skills’, since the latter are not really requirements for a profession to perform its task. After these steps, the refined list compiled 595 digital skills out of 8,522.

The fourth step was to measure the intensity of digital skills required by each ISCO 3-dig occupation. An occupation may require a specific amount of digital skills among all the skills needed to perform its tasks. The equation below measures the digital skills intensity of each ISCO 3-dig occupation, ranging from 0 to 100%.

$$Dig\ skills\ intensity_i = \left(\frac{X_i}{T_i}\right) * 100$$

Where *i* is an occupation ISCO 3-dig; Dig skills intensity represents the intensity of digital skills in percentage; *X* is the number of digital skills required; and *T* is the total number of skills required.

Based on the above indicator, we grouped the occupations into four categories according to the intensity of their digital skills. The grouping criteria were as follows:

1. **High digital skills:** when at least 20% of the occupation's skills are digital skills;

2. **Medium digital skills:** when the proportion of digital skills ranges from 5% to 19.99% of the total set of skills in the occupation;
3. **Low digital skills:** when the proportion of digital skills varies between 0.01% and 4.99% of the total set of skills in the occupation;
4. **Non-digital skills:** occupations that do not require any digital skills.

Other studies that analysed the skills profile of occupations relied on the description of the skill to categorise them, for example, as cognitive occupations, soft occupations, low-skilled occupations, etc. (Acemoglu and Autor, 2010; Autor and Dorn, 2013; Bacolod *et al.,* 2009, 2010; Ehrl and Monasterio, 2019; Tessarin *et al.,* 2020) without adding intensities within those categories. To the best of our understanding, previous studies that have evaluated digital skills also took into account only whether an occupation is digital or not, without further qualification within the group (Castellacci *et al.,* 2020; Consoli *et al.,* 2023). Taking an innovative approach, we created three categories of digital-skills intensity based on the relative importance of digital skills in proportion to the total skills demanded by an occupation. Similarly, Soh *et al.* (2022) also used a threshold based on percentage points of digital skills to classify digital professions in the United States.

Finally, we connected this list of digital skill intensity by ISCO-08 3-dig occupation with the occupation and region data from the LFS.

It is important to underline that this is the first attempt to develop a measure of the relative importance of digital occupations and, therefore, it is open to improvement. Unlike O*Net (the Dictionary of Occupational Titles available in the USA), ESCO dos not include a measure of the importance of a skill to an occupation, so there is no way to base it on a pre-established criterion of the order of importance of skills to an occupation.

3.2.3. Digital trademarks

Trademarks are classified by classes according to the Nice Classification, which assigns goods to classes 1 to 34 and services to classes 35 to 45. Each class contains a set of terms providing general information about the type of goods or services to which the application refers. Some definitions are narrower and can be clearly related to a market, while others encompass a wide range of goods or services. For example, class 15 denotes “Musical instruments; music stands and stands for musical instruments; conductors' batons”, while class 18 is a broader one, covering “Leather and imitations of leather; animal skins and hides; luggage and carrying bags; umbrellas and parasols; walking sticks; whips, harness and saddlery; collars, leashes and clothing for animals”.

To classify trademarks related to digital markets and assets, we rely on the report prepared in collaboration between the JRC and OECD regarding the digital economy (Daiko *et al.,* 2017). The report identified classes containing keywords related to information and communications technologies (ICT) in the descriptions of the goods and services to classify trademark classes as “digital trademarks”.

Table 2 displays the six selected classes. In our report, all other classes were classified as non-digital to contrast with digital trademarks.

Table 2 - Nice classes classified used to identify digital trademarks

Nice Class	Description
9	Scientific, nautical, surveying, photographic, cinematographic, optical, weighing, measuring, signalling, checking (supervision), life-saving and teaching apparatus and instruments; apparatus and instruments for conducting, switching, transforming, accumulating, regulating or controlling electricity; apparatus for recording, transmission or reproduction of sound or images; magnetic data carriers, recording discs; compact discs, DVDs and other digital recording media; mechanisms for coin-operated apparatus; cash registers, calculating machines, data processing equipment, computers; computer software; fire-extinguishing apparatus
28	Games, toys and playthings; video game apparatus; gymnastic and sporting articles; decorations for Christmas trees
35	Advertising; business management; business administration; office functions
38	Telecommunications
41	Education; providing of training; entertainment; sporting and cultural activities
42	Scientific and technological services and research and design relating thereto; industrial analysis and industrial research services; design and development of computer hardware and software

Source: Daiko *et al.* (2017).

A single trademark application may mention more than one Nice class related to the purpose of the product or service. We chose to consider all classes indicated in an application to account for the share of digital and non-digital trademarks classes, therefore, no fractional counting was applied.

3.3. Operationalising the evolutionary approach to regional economic resilience

3.3.1. Relatedness and relatedness density

A key concept that we use in our analysis is *relatedness*. We calculated relatedness and relatedness density using both occupation and trademark data.

We estimate the relatedness by examining the probability of two occupations co-occurring in the same region. Relatedness indicates the probability that a region specialises in an occupation *a*, given that it also specialises in an occupation *b*. Occupational relatedness in a period is a standardised measure of the frequency of two occupations appearing in the same region with RCA (Juhász *et al.,* 2021). High relatedness values indicate that two occupations are more frequently combined, while low relatedness values suggest that the occupation pairs are relatively independent (Tessarin *et al.,* 2023c).

As we have 130 ISCO codes for occupations in total in our dataset, we obtain a 130x130 matrix of proximities for occupation. As for trademarks, we have 45 Nice classes; then, we obtain a 45x45 matrix of proximities for trademarks.

We created the occupation and trademark spaces after calculating the relatedness based on co-occurrence for occupations and trademarks. The network or space is a representation of links and nodes based on the proximity between the occupations or trademarks. We applied the Jaccard[7] normalisation mode to calculate the relatedness.

To link relatedness with the economic structure of the regions, we calculated the relatedness density (RD) following Hidalgo *et al.* (2007). The values of RD range between 0 and 1, where high values indicate a higher proportion of related occupations/markets in which a region is already specialised. Intuitively, our measure of relatedness density then captures, for each occupation/trademark class, whether and to what extent the same region is also specialised in related occupations/trademark classes. In this way, we can effectively capture the structure of the region and measure whether relevant and supportive capabilities are locally present.

RD represents the distance between an occupation/trademark and the existing occupational/market structure in a region. In this sense, we can indicate the most probable diversification paths based on the existing resources in each region. These concepts fit in with the concepts of resilience, especially adaptation and renewal, which indicate possible alternatives for recovery after shocks.

We calculated the RD indicators for urban and non-urban regions using the eleven occupations classified as high digital skills intensity as well as the six trademark classes classified as digital.

3.3.2. Regional resilience: The sensitivity index

Many studies assessing the resilience of regions to external shocks (such as the 2008 global financial crisis) use mainly two indicators: Sensitivity index (SI), a proxy for the resistance of a region to a shock,

[7] The Jaccard method is based on the proportion of nodes shared between A and B in relation to the total number of nodes connected to A or B. Thus, we consider this method to be more suitable because it provides a weighted measure relative to the total number of nodes in the network.

and Response index (RI), a proxy for its capacity to recover from a shock (Faggian *et al.,* 2018; Filippetti *et al.,* 2020; Martin, 2012).

SI is calculated by considering the period of the shock in relation to a previous period, while RI requires a period after the shock that is not so distant but sufficiently able to capture recovery (Faggian *et al.,* 2018). As we do not yet have data available for all European regions at NUTS 2 digits to calculate the effect of RI at the moment, we will calculate the SI to qualify the resilience of the regions during the shock.

According to Filippetti *et al.* (2020), Sensitivity index (SI) is calculated as follows:

$$SI = \frac{\left(\frac{Occup_{r,t}}{Occup_{r,t-1}}\right)}{\left(\frac{Occup_{n,t}}{Occup_{n,t-1}}\right)}$$

Where SI measure the relative performance of a region compared to the average performance of the EU; *Occup* is the share of an occupation, *r* is the region, *n* represents the EU average; *t* is the average for 2020-2021 (the pandemic period); and as for *t-1* we use the average for 2018-2019 (immediately before the pandemic period).

We calculated SI for each group of occupations by digital skills intensity, for CCOs, and digital and non-digital trademarks – in the case of trademarks, replace *Occup* with *TM_Classes* in the equation above, representing the total number of trademark classes.

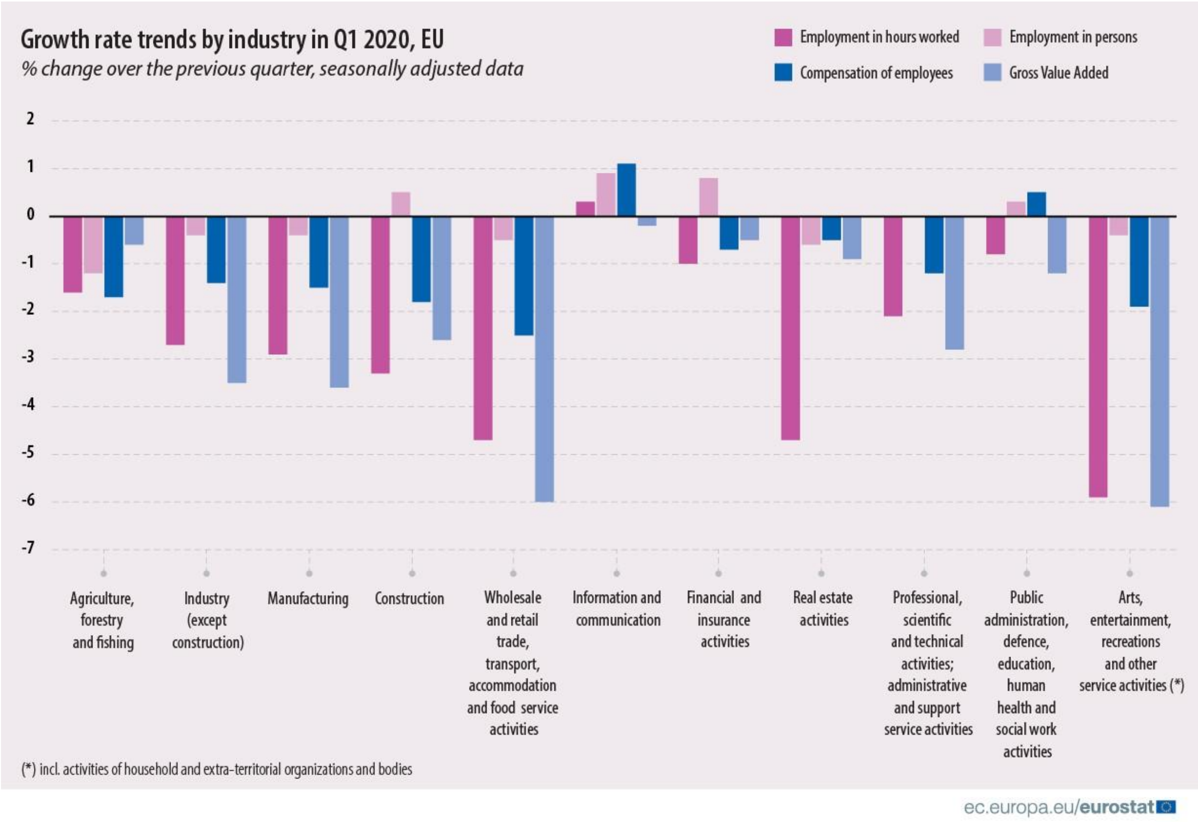
4. Results

4.1. Introduction to the analysis

The COVID-19 pandemic has disrupted the life, work and organisation of virtually every community on the planet. On top of that, the pandemic negatively affected global economic growth in 2020 and 2021. Measures restricting movement and international travel, social distancing, lockdowns and so many others have had an immediate and severe impact on the economies of countries.

To introduce our analysis, we use data from Eurostat to provide some contextual information on the impact of the pandemic. Figure 1 – provided by Eurostat – shows that all sectors of economic activity in the 27 European Union countries suffered an immediate contraction in economic activity in the first quarter of 2020.

Figure 1 - Growth rate by industry in the European Union – Q1 2020 (%)



Source: Eurostat (2020).

The most significant decline in the growth rate of GVA (Gross Value Added) in the first quarter of 2020 was seen in “arts, entertainment, recreation and other service activities” (-6.1%), followed by “wholesale and retail trade, transportation, accommodation and food service activities” (-6.0%), which were the sectors most affected by the shutdowns to contain the spread of COVID-19.

In terms of hours worked, “arts, entertainment, recreation and other service activities” also recorded the biggest drop among all sectors (-5.9%), followed by “wholesale and retail trade, transportation, accommodation and food service activities” and “real estate activities” (-4.6% in both). However, the negative impact on the growth rate was widespread and was also felt in the agriculture, industry, manufacturing, professional, scientific and technical activities, as we can see in Figure 1 from Eurostat.

Only “information and communication” activities showed a different trend in this period. In this sector, the number of employed people increased (+0.9%), as did the wages (+1.1%).

As lockdown measures persisted in the second quarter of 2020, the European economy contracted further at an unprecedented pace. Analysis of sector data for the second quarter of 2020 shows that the arts, recreation and other service activities were among the hardest-hit sectors (Voldere *et al.*, 2020). Compared to the previous period (Q2 and Q1 quarters), arts and recreation saw the second-largest drop in employment of all sectors and a significant reduction in gross value added (Voldere *et al.*, 2020).

In this context, and to try to survive the pandemic, the creative and cultural sector has tried to reinvent itself. One of the options has been to implement or intensify the use of digital tools (Brooks and Patel, 2022; Jeannotte, 2021; Noehrer *et al.*, 2021; Voldere *et al.*, 2020). Digital technologies and capacities have drastically changed how cultural and creative goods and services are produced, distributed and consumed. However, while for some cultural and creative organisations, the switch to digital formats was easy due to the availability of in-house expertise; for many others, the adoption of digital solutions was not an easy path to follow (Khlystova *et al.*, 2022; Voldere *et al.*, 2020).

In some sub-sectors, activities could continue more or less normally, especially where creative outputs and services are digital, or the production and distribution processes could be easily digitised (Voldere *et al.*, 2020). Examples of this are the radio and television broadcasting and games sub-sectors. Although experiments with new forms of distribution (e.g., electronic distribution) or presentation (online or small-scale and local) have not compensated for the drastic reduction in revenues, they have helped these sub-sectors to reconfigure themselves and withstand the strongest period of lockdown and social distancing.

Below, we present results that show how digital capabilities in terms of employment and markets have worked as distinctive elements in the regions during the COVID-19 pandemic. The results are presented first with a focus on digital skills and occupations and second on digital markets and trademarks. Following this, we calculate indicators of regional resilience during the pandemic and in the final sections, we present potential paths for regional recovery based on digital capabilities.

4.2. Profile of occupations by skill

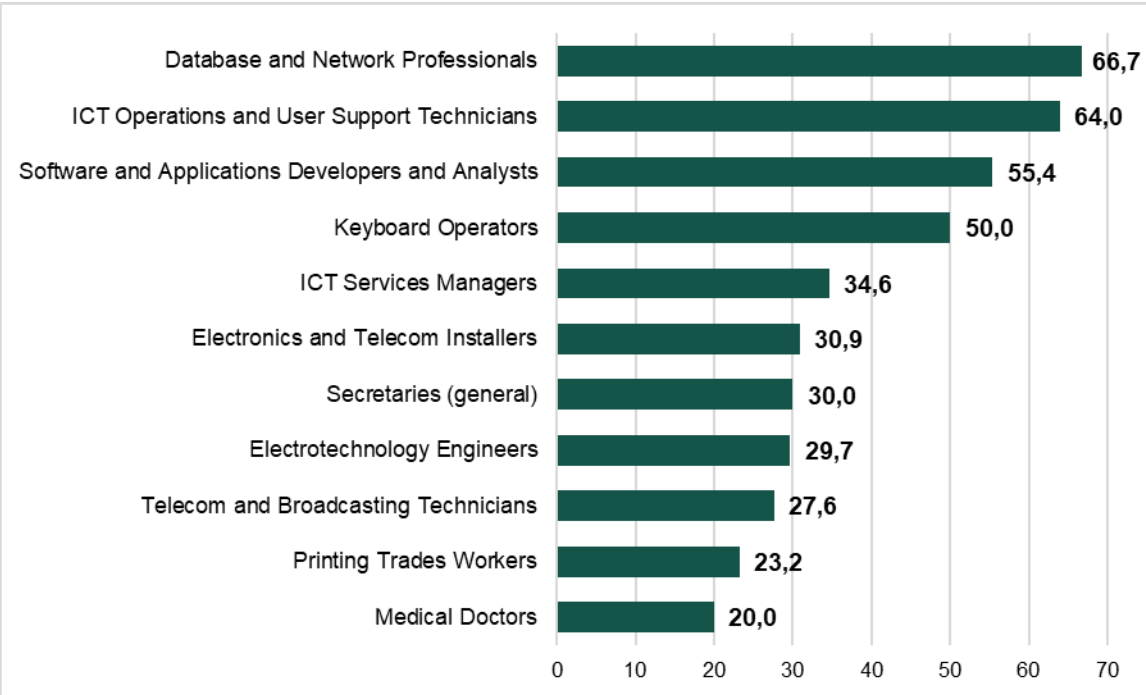
Each occupation comprises a unique set of skills, and the number of skills per occupation varies. It depends on the requirements and tasks related to each occupation – for example, one might develop more manual and dexterity skills, others would require more social skills, while still others might demand more cognitive skills to solve complex tasks. Digital skills are one of these groups within the set of possibilities. As explained in Section 3.2.2, digital skills involve, for instance, information and data literacy, communication and collaboration, media literacy, digital content creation and programming, cybersecurity, intellectual property, problem-solving and critical thinking (European Commission, 2022).

To understand the profile of occupations, we first classified them according to the intensity of digital skills. The figures in this section show the proportion of digital skills (also called "dig-skills") in relation to the total number of skills required by each occupation for all 130 occupations at the ISCO 3-digit level.

We have divided the occupations into four groups according to their digital skills intensity: high, medium and low digital skills intensity and occupations that do not require digital skills.

Figure 2 shows the occupations classified as having a high intensity of digital skills, that is, those in which at least 20% of the skills in the occupation refer to digital skills. In this category, there are 11 occupations in total, four of which have a proportion of digital skills above 50%: Database and Network Professionals; Information and Communications Technology (ICT) Operations and User Support Technicians; Software and Applications Developers and Analysts; and Keyboard Operators. Occupations with a high intensity of digital skills include not only developers of products and services related to new technologies – especially in the ICT area – but also users who must know and incorporate the use of these technologies when performing their tasks, such as telecommunications and broadcasting technicians, printing trades workers and medical doctors.

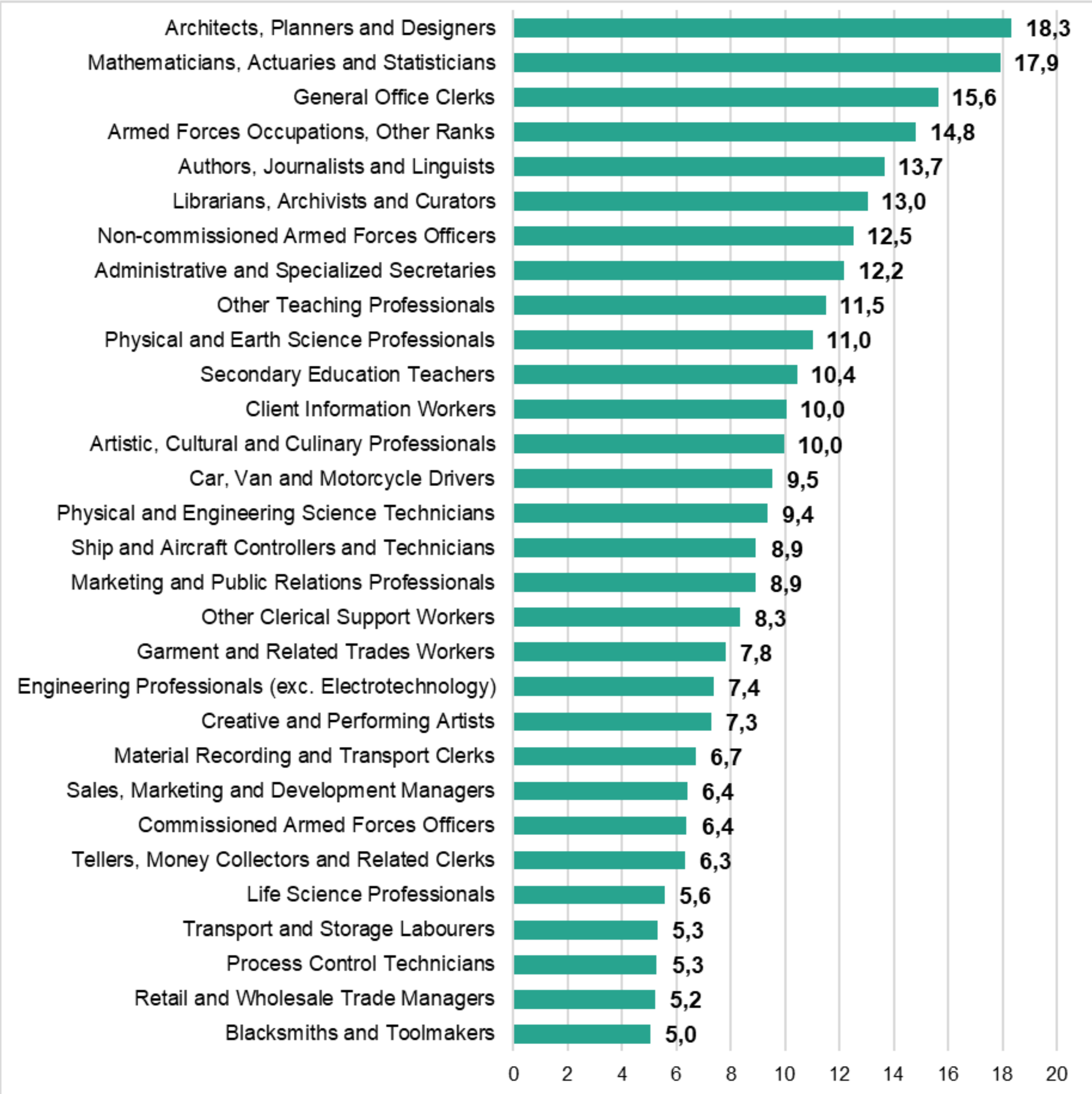
Figure 2 - High-intensity digital skills occupations: share of digital skills in total skills (%)



Source: Authors' elaborations based on ESCO.

Figure 3 shows the occupations classified as medium intensity in digital skills in relation to the total skills required to perform their job. There are 30 occupations in which the proportion of digital skills ranges from 5% to 19.99% of total skills. In this group, 13 occupations have at least 10% digital skills, and the remainder (17 occupations) range from 5% to 9.99%.

Figure 3 - Medium-intensity digital skills occupations: share of digital skills in total skills (%)



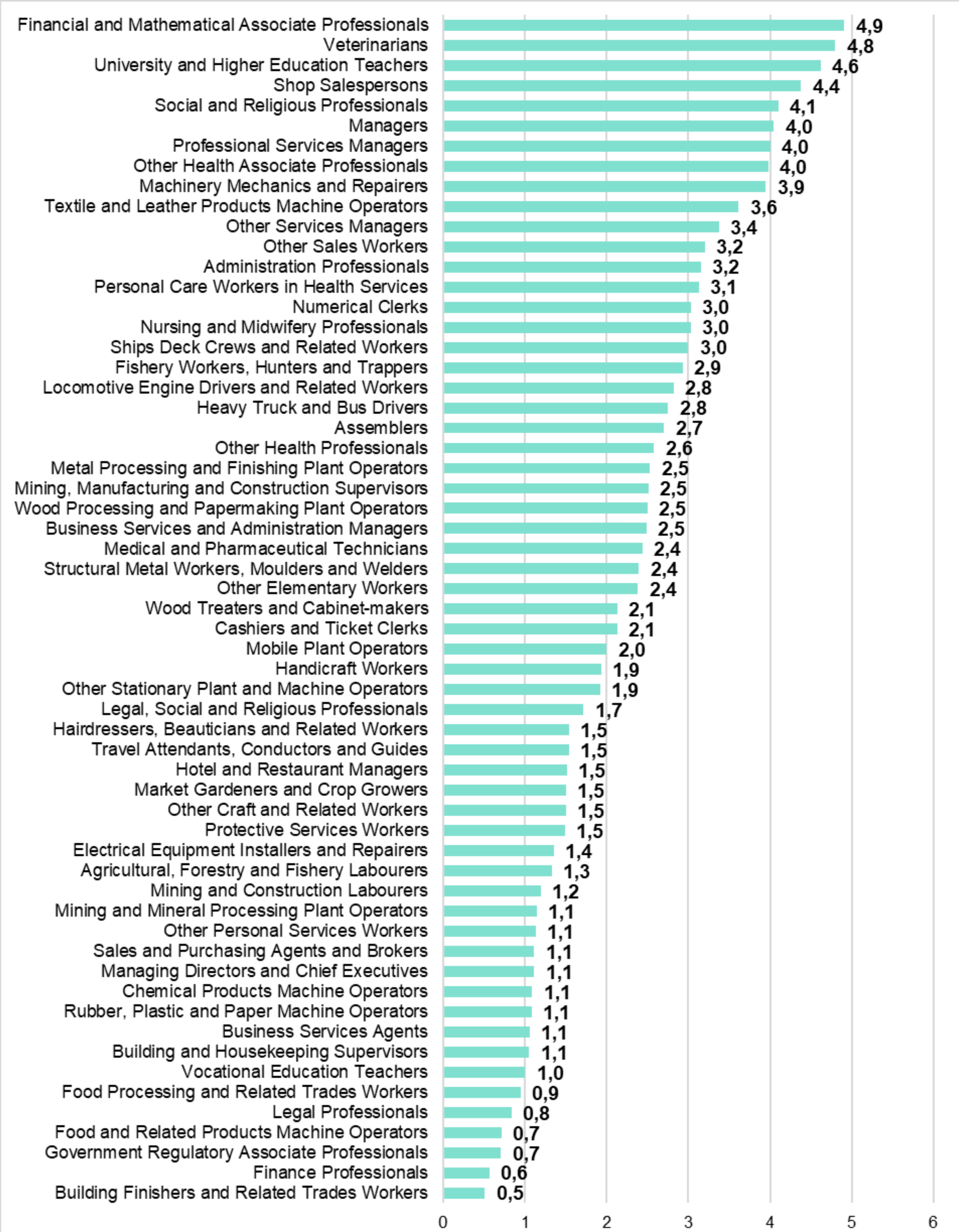
Source: Authors' elaborations based on ESCO.

Interestingly, some occupation classes that may be expected to use digital skills intensively (for instance, architects or mathematicians) belong to this second class. While this is due to the specific threshold we selected, and effectively, these groups rely somewhat regularly on digital skills, a possible explanation may have to do with the number of different tasks these occupations need to perform. Architects and mathematicians require a much higher number of skills and varying types (much higher, for example, than medical doctors). Therefore, in these cases, the digital part is diluted among a multitude of other skills. In addition, the ISCO code for medical doctors covers only two subclasses (generalist and specialist doctors), while the other ISCO code covers in the category "architects", architects, planners, surveyors and designers, and in the category "mathematicians", mathematicians, actuaries and statisticians, i.e., a larger set of professionals who probably require different types of skills.

Figure 4 shows the occupations classified with the lowest intensity of digital skills. It contains 59 occupations with digital skill intensity ranging from 0.5% to 4.99% of each occupation's total skill set.

Several occupations are related to many industries and work fields in the low digital skills intensity group. For example, healthcare occupations which require proportionally more other types of skills (social and cognitive) – such as health associate professionals, personal care workers, and nursing and midwifery professionals. There are also occupations requiring competences with quantitative data, such as financial and mathematical associate professionals and numerical clerks. Other occupations in this group give greater relevance to manual skills and dexterity, such as handicraft workers; machinery mechanics and repairers; textile and leather products machine operators; wood processing and papermaking plant operators; and other kinds of machine operators.

Figure 4 - Low-intensity digital skills occupations: share of digital skills in total skills (%)



Source: Authors' elaboration based on ESCO.

Finally, there is a group of 30 occupations where none of the digital skills are relevant to their tasks. Therefore, they have been classified as occupations with non-digital skills. Non-digital skills occupations involve, for example, professionals dedicated to agriculture, forestry, fishing, and livestock activities. On this list is a group of professionals related to the provision of leisure services, such as hotels, sports and restaurants – such as sports and fitness workers; cooks; waiters and bartenders; and food preparation assistants. The complete list of occupations in this group is presented in Appendix B.

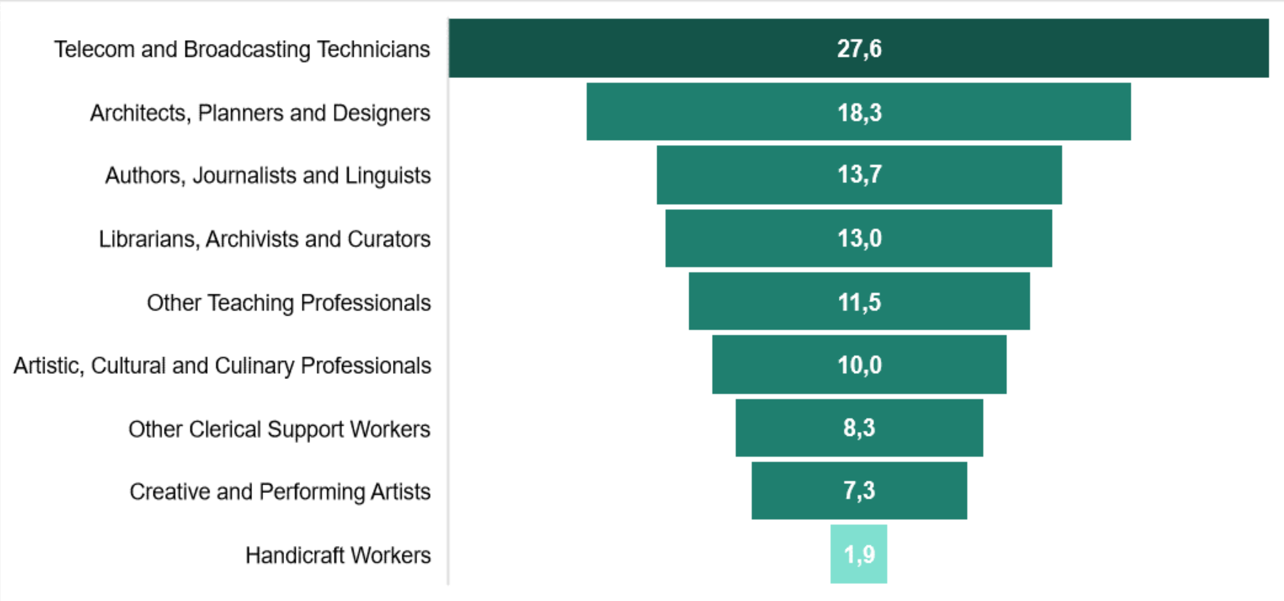
In summary, there are 100 occupations at the ISCO 3-digit level that require at least 1 digital skill to perform the tasks linked to them and 30 occupations that do not require any digital skills. Therefore, digital content is present in 3 out of 4 occupations, albeit in different intensities, as shown in Figures 2 to 4.

Going deeper into the occupations, we selected only those classified as cultural and creative occupations (CCO) as we wanted to understand whether these occupations require a high proportion of digital skills to perform their tasks.

As we can see in Figure 5, only one CCO is classified as high dig-skill (telecommunications and broadcasting technicians). At the same time, handcraft workers are the only CCO classified as low dig-skills. Thus, the majority of CCOs are classified as medium dig-skills (seven in total), with at least a digital skills intensity of 7.3%.

Two-thirds of the total occupations (89 out of 130) have low digital skills intensity or do not require any digital skills at all. On the other hand, the CCO group has a profile that requires more digital skills than the average occupation in general.

Figure 5 - Digital skills intensity of CCO: share of digital skills in total skills (%)



Source: Authors' elaborations based on ESCO.

In Section 4.2, we have characterised the occupations by the intensity of digital skills. Section 4.3 looks at the distribution of jobs in each group over the last few years.

4.3. Jobs with digital skills in the European labour market

As we saw earlier, occupations can be divided into four groups by the intensity of the digital skills needed to carry out their activities. Here, we analyse the relative participation of each of the four groups of occupations over the last eight years (from 2014 to 2021), including years before and during the pandemic, in the context of the European Union.

We started the analysis in 2014 to maintain a balanced sample of regions since, between 2011 and 2013, some countries adjusted their regional division, and data was unavailable for all regions.[8] We

[8] We are working with the 2008 version of ISCO (ISCO-08), available since 2011 in the LFS statistics.

analysed the period of the COVID-19 pandemic considering the years 2020 and 2021, as there is still no data for subsequent years.

The pandemic has changed how people work, requiring many occupations to be transformed to adapt to social distancing norms and consequently use more digitalised tasks and activities. At the same time, the shock caused by the pandemic was exogenous (not expected); therefore, there was no time for training and adjustments in how goods and services were offered. All the changes took place in an uncertain scenario and on the basis of experimentation. In this sense, our central hypothesis is that occupations that already required a set of digital skills before the pandemic were better able to adjust quickly to new or unforeseen demands.

Of course, occupations with other non-digital skills have also had to reinvent or readjust themselves. In this case, we believe there was a greater barrier to overcome in terms of reinventing how they offered services and carried out their activities in the two most acute years of the crisis (2020 and 2021). Therefore, our hypothesis is that workers in those occupations faced more significant challenges in coping with the pandemic and were relatively more affected than the group of occupations with higher intensity of digital skills.

To meet the objectives of this project, we compare non-urban European regions (Section 4.3.1) with urban ones (Section 4.3.2). First, we analyse occupations in general and then look exclusively at cultural and creative occupations within a regional context.

4.3.1. Digital skills occupations in EU non-urban regions

This Section seeks to verify whether there have been changes in the relative distribution of occupations by the intensity of digital skills before and during the COVID-19 pandemic. Figure 6 shows this distribution for the non-urban regions of the European Union.

Although there are small changes over the period 2014 to 2021 in the distribution of occupations by the degree of digital skills (Figure 5), there is considerable stability in the share of groups with digital skills.

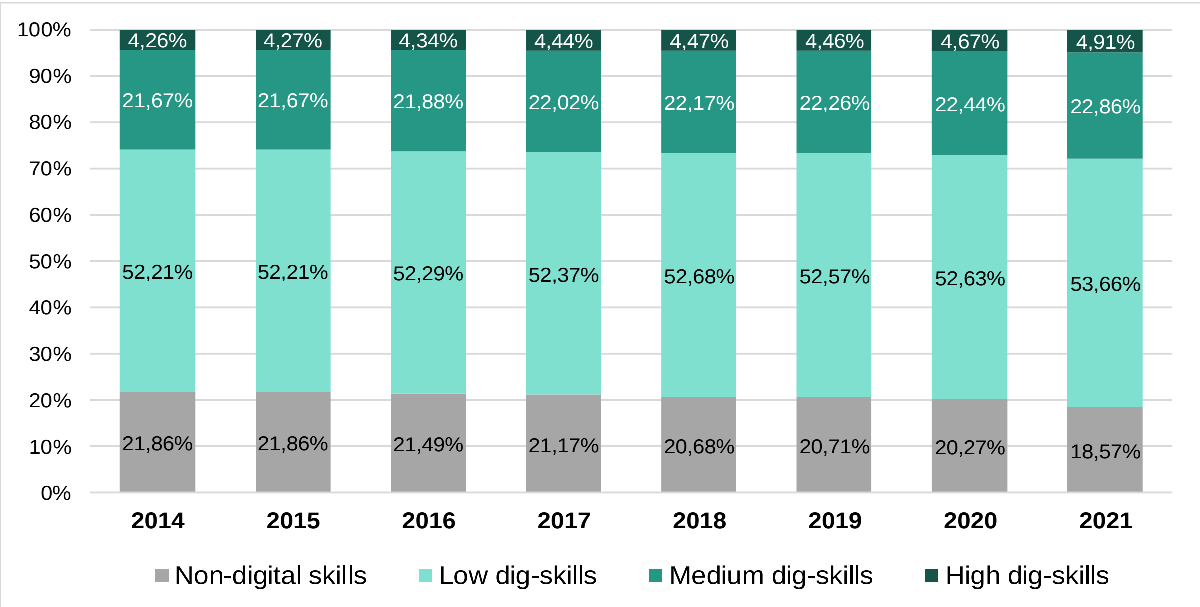
Low digital skills occupations account for between 52% and 54% of all occupations in the EU's non-urban regions. Next, medium digital skills occupations hold between 21% and 23% of total occupations. High digital skills occupations have a smaller share, oscillating between 4% and 5% of total jobs in non-urban regions.

In turn, non-digital occupations, that is, occupations that do not require digital skills, represent between 18% and 21% of occupations on average over the period. Such stability is expected because the labour market is heavily influenced by structural factors (for example, industrial composition), which do not change rapidly in the advanced economies of the EU.

As for the main relative changes, we noticed a greater difference in non-digital occupations (Figure 6). This group of occupations has been losing percentage share over the years analysed, but the most significant drop was seen between 2020 and 2021. Between 2014 and 2021, this group shrank by 3.29 percentage points (p.p.). In the pandemic period, it decreased by 0.44 p.p. in 2020 and 1.7 p.p. in 2021; so in the two years of the pandemic, it lost 2.14 p.p., going from 20.71% in 2019 to 18.57% in 2021.

When comparing 2021 with 2019 to capture the changes during the pandemic, we see that the greater the intensity of digital skills, the greater the percentage increase in the relative share among these groups. Between 2019 and 2021, the low dig-skills occupation group increased by 2.07% (from 52.57% to 53.66%), the medium dig-skills group increased by 2.70% (from 22.26% to 22.86%), and the high dig-skills group increased by 10.09% (from 4.46% to 4.91%). This data confirms our central hypothesis that occupations that already required a set of digital skills prior to the pandemic were better able to adjust quickly and gained market participation during the pandemic.

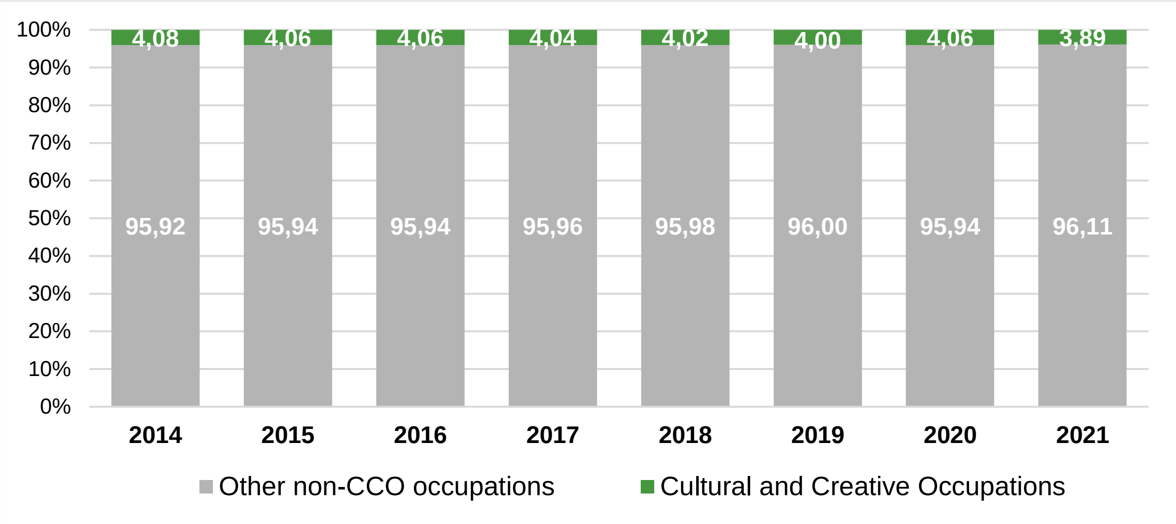
Figure 6 - Distribution of occupations by digital skills intensity in non-urban regions



Source: Authors' elaborations based on LFS and ESCO.

To address only cultural and creative occupations (CCOs) in non-urban regions, we first sought to identify the share of CCOs in total employment in that region. Figure 7 shows that around 4% of total employment in non-urban regions is made up of CCOs, a stable share between 2014 and 2020. However, the shock of the pandemic was felt in 2021, when the CCO share dropped by almost 0.1 percentage point or about 4.19% (from 4.06% to 3.98%).

Figure 7 - Share of CCO in non-urban region

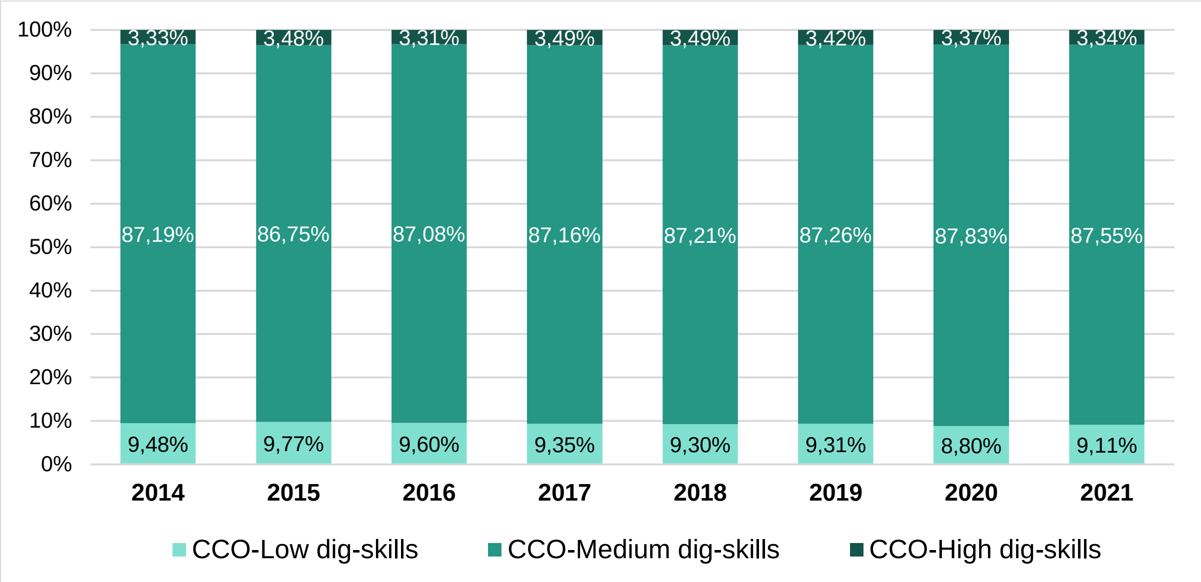


Source: Authors' elaborations based on LFS.

We now move on to analyse the intensity of digital skills within this subset of CCOs (Figure 8). As we saw in Figure 5, seven of the nine CCOs are medium dig-skills occupations, representing just over 87% of the total. Adding up the medium and high digital skills represents 90% of the total CCO in non-urban regions.

In the two years of the pandemic, on one hand, we noticed a slight increase in the share of the medium dig-skills intensity group, from 87.26% in 2019 to 87.55% in 2021 of all CCOs. On the other hand, the CCOs classified as low dig-skill showed a slight drop in participation during the pandemic period, going from 9.31% in 2019 to 8.8% in 2020 and 9.11% in 2021, the lowest percentage values of the entire period.

Figure 8 - Distribution of CCO by digital skills intensity – non-urban regions



Source: Authors' elaborations based on LFS and ESCO.

In Section 4.3.2, we analyse the scenario for urban regions in the European Union to see if there are any differences with the results for non-urban regions.

4.3.2. Digital occupations in EU urban regions

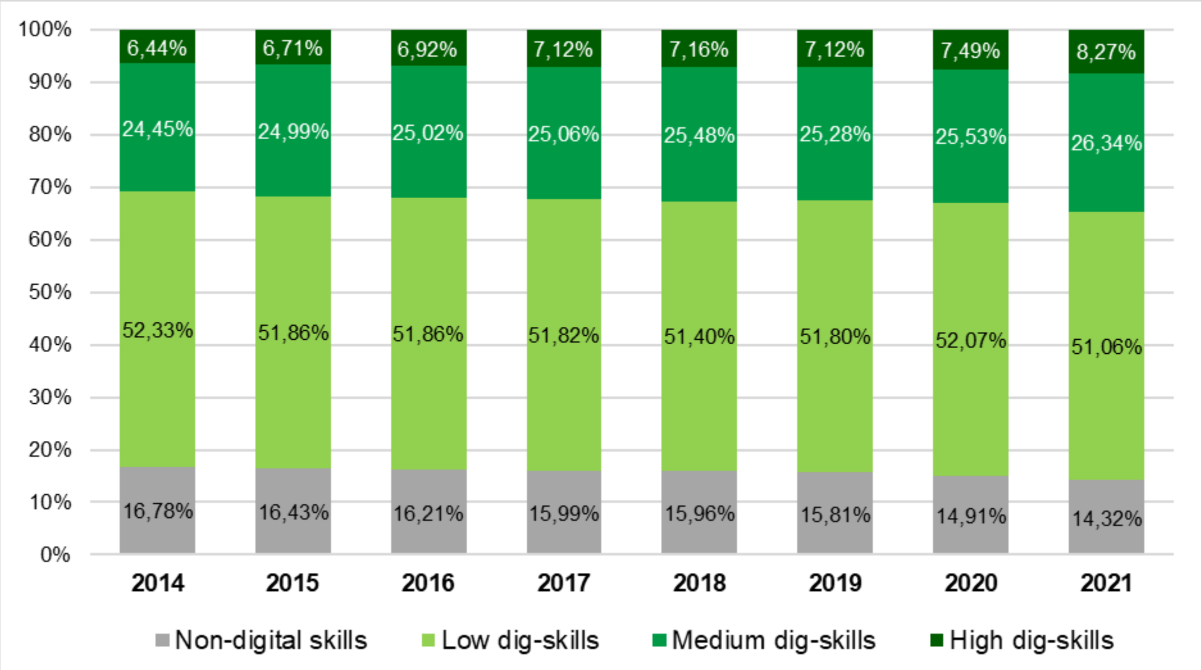
When comparing the distribution of occupation groups by intensity of digital skills in urban regions (Figure 9) and non-urban regions (Figure 6), we can see that the share of medium and high dig-skills intensity is higher in urban regions. In addition, the share of non-digital skills occupations is higher in non-urban regions. In turn, the share of the group of low-dig skills intensity is similar in both regions.

Therefore, we can assume that urban regions have a productive structure that is more oriented towards activities that demand occupations with a higher intensity of digital skills than non-urban regions. In general, urban regions tend to host the digital activities of large companies, which demand occupations with medium and high digital skills intensity.

As for the relative changes in the period before and during the pandemic, we noticed that the greater the intensity of digital skills occupations, the greater the percentage increase in the composition of jobs.

On one hand, between 2019 and 2021, non-digital skills occupations declined by 9.42% (from 15.81% to 14.32%) and low dig-skills occupations by 1.43% (from 51.80% to 51.06%). On the other hand, medium dig-skills occupations increased by 4.19% (from 25.28% to 26.34%) and high dig-skills occupations increased even more, by 16.15% (from 7.12% to 8.27%).

Figure 9 - Distribution of occupations by digital skills intensity in urban regions

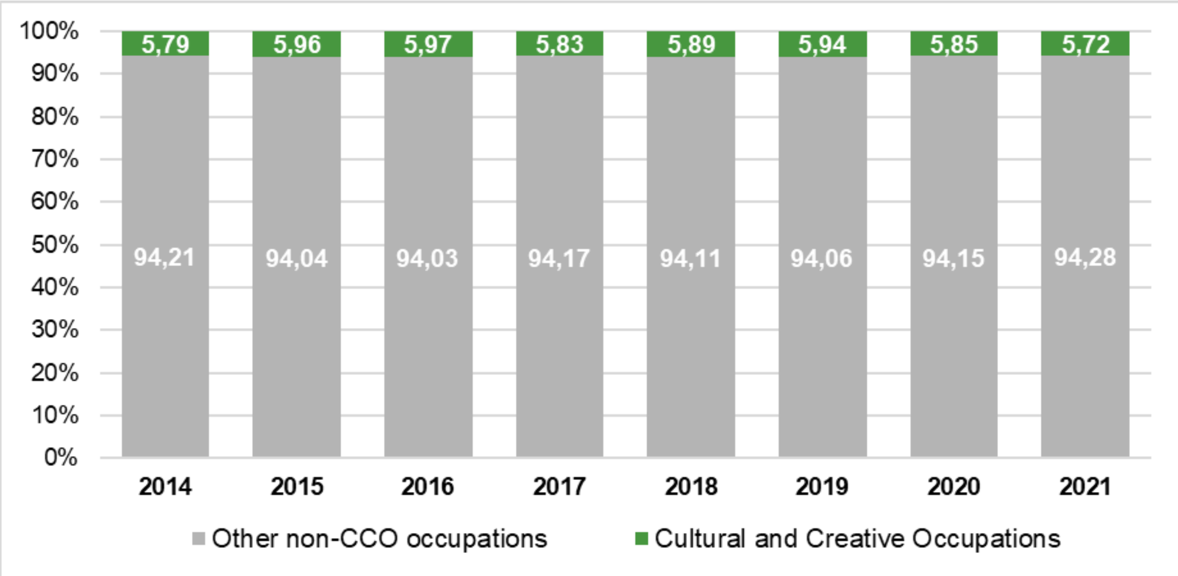


Source: Authors' elaborations based on LFS and ESCO.

Thus, the relative change in jobs with greater intensity of digital skills was positive and more intense in urban regions than in non-urban regions. At the same time, the relative reduction in occupations requiring non-digital skills was also greater in urban regions during the pandemic years. These data again confirm our central hypothesis mentioned earlier, and with greater weight than in non-urban regions.

Next, we look only at CCOs in urban regions (Figure 10). In this context, CCOs represent almost 6% of all occupations. With the pandemic shock in 2020, this share dropped from 5.94% in 2019 to 5.85% in 2020 and 5.72% in 2021, the lowest percentage in the period analysed.

Figure 10 - Share of CCO in urban region



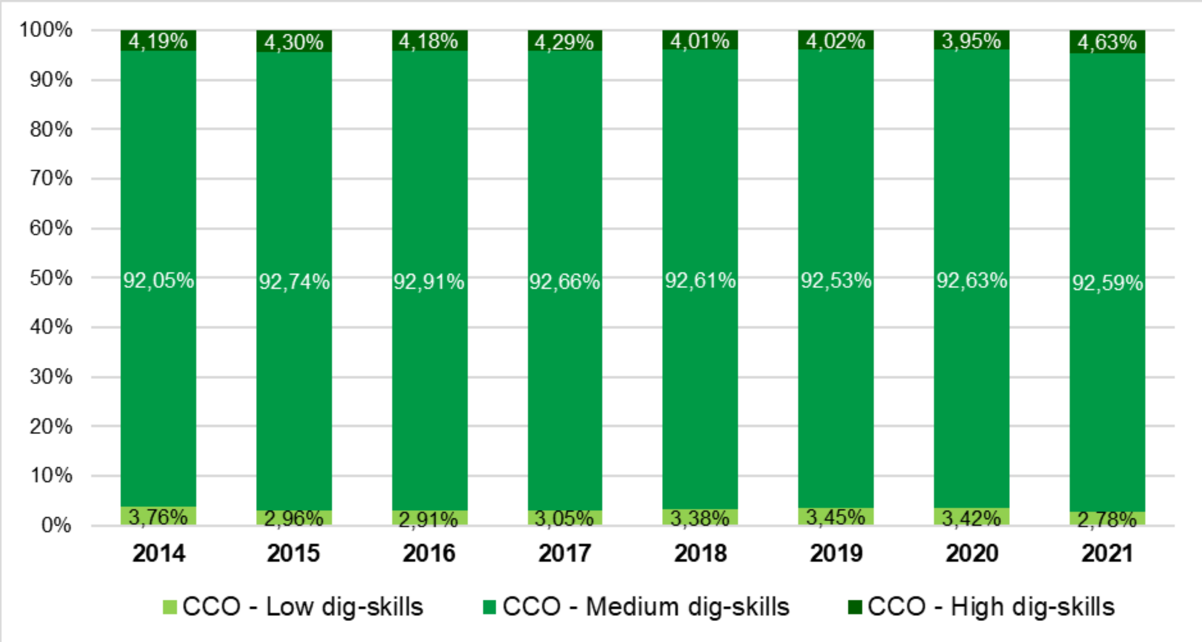
Source: Authors' elaborations based on LFS.

When comparing urban and non-urban regions during the pandemic, we noticed that the drop in the share of CCO in urban regions was greater than in non-urban regions. While in urban regions, the reduction was 3.70% (from 5.94% to 5.72%) between 2019 and 2021, in non-urban regions the drop was 2.75% (from 4.00% to 3.89%). Thus, non-urban regions were more resilient in maintaining the share of CCOs in relation to the total occupations.

We then analysed how the intensity of digital skills is distributed among CCOs in urban regions. Figure 11 shows that CCOs with a medium intensity of digital skills represent the largest share of CCOs in the urban context, and together with CCOs with a high dig-skills intensity, they make up more than 95% of CCOs.

In urban regions, low dig-skills CCOs dropped their relative share during the pandemic years (from 3.45% to 2.78%, i.e., a reduction of 0.67 percentage points). The opposite was true for high dig-skills CCOs (from 4.02% to 4.63% between 2019 and 2021, a gain of 0.61 percentage points). The largest group, medium-digital skills intensity, showed a marginal increase of 0.06% (from 92.53% to 92.59%).

Figure 11 - Distribution of CCO by digital skills intensity in urban regions



Source: Authors' elaborations based on LFS and ESCO.

When comparing the period before and during the pandemic in non-urban regions (Figure 8) and urban regions (Figure 11), we noticed that in urban regions, there was an expansion of 15.17% in the high dig-skills group (from 4.02% to 4.63%) compared to a reduction of 2.34% in non-urban regions (from 3.42% to 3.34%) between 2019 and 2021. In the low dig-skills group, there was a drop in both regions, of 19.42% in urban regions (from 3.45% to 2.78%) and 2.15% in non-urban regions (from 9.31% to 9.11%). In the medium dig-skills group, both regions had a marginal increase.

Therefore, the intensity of digital skills in the CCOs played a more relevant role in urban than non-urban regions during the pandemic.

4.4. Resilience of regions during the pandemic in terms of digital occupations

The pandemic has had several waves that have hit regions and occupations at different times and intensities. For this reason, in this section, we conduct a more detailed analysis of the 2-digit NUTS regions. We focus on the socio-economic resilience of regions during the pandemic, taking an evolutionary perspective on regional resilience. To this end, we evaluate the performance of the regions compared to the years immediately before (2018 and 2019) and the years of the pandemic (2020 and 2021).

The scatter plots below show the position of the NUTS 2-digit regions in the period before and during the pandemic. Each point on the graph represents a NUTS region. The x-axis shows the average share of occupations in each NUTS region in 2018 and 2019 (pre-pandemic). The y-axis shows the average share for 2020-2021 (pandemic). Each figure is based on the four groups of digital skills intensity. From the 45-degree line, which starts at the origin, we can separate the regions that grew more or less in the second period compared to the first. In other words, regions positioned above the line (blue colour) managed to increase the percentage share of occupations even in the years of the pandemic. On the other hand, regions positioned below the line (red colour) did not have the same success and reduced the share of occupations in the years of the pandemic.

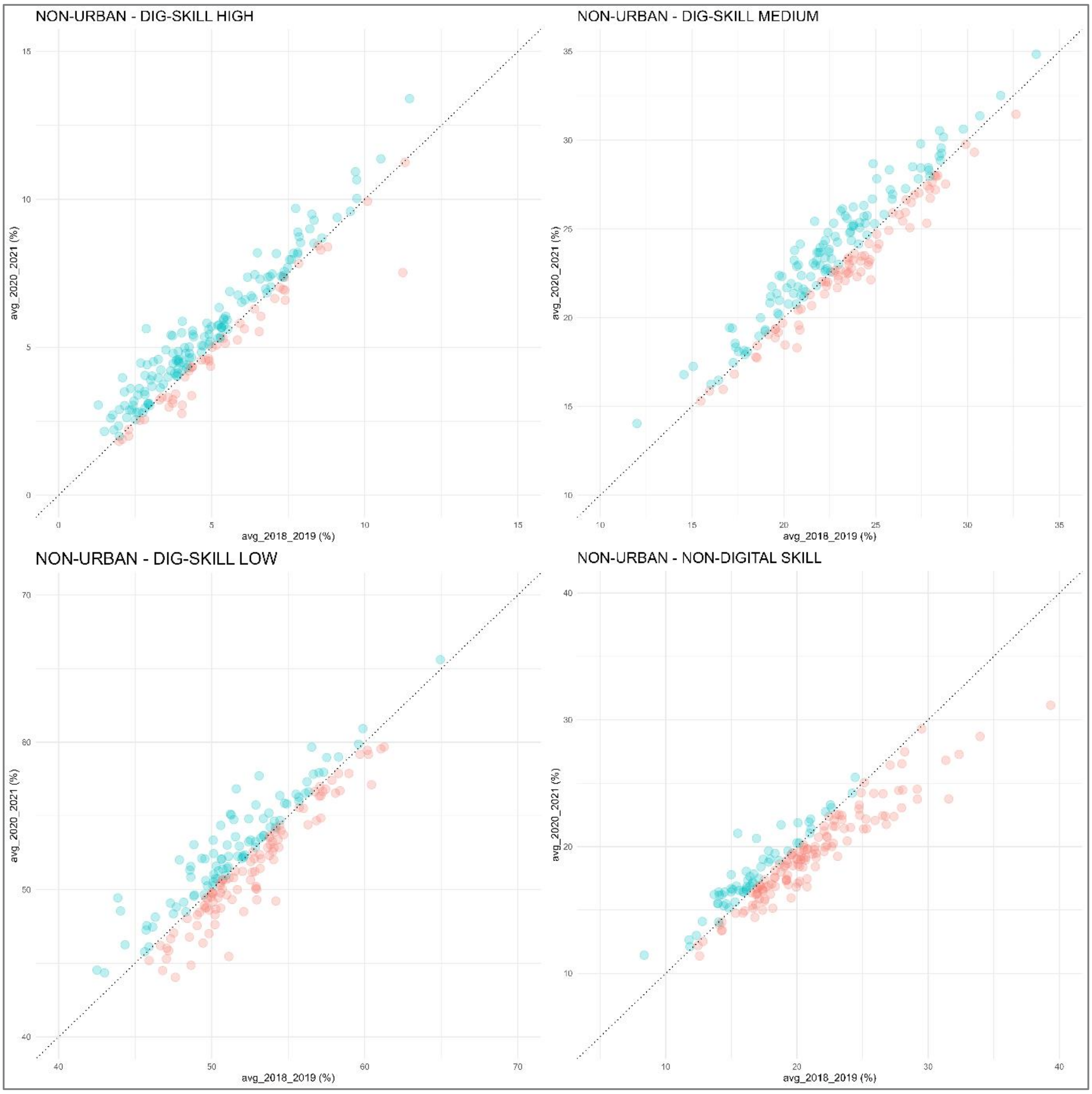
In addition to sorting urban and non-urban regions, we divided occupations by digital skills intensity to identify possible differences before and during the pandemic. Our hypothesis is that occupations with a higher intensity of digital skills adapted more quickly to the pandemic shock and were more resilient during the pandemic years. In this sense, regions with a higher percentage of occupations with a high level of digital skills should be more resilient.

The first set of graphs (Figure 12) shows the performance of non-urban regions and divisions by the intensity of digital skills, starting with high (top-left), medium (top-right), low (bottom-left) and finally, non-digital skills (bottom-right).

Our expectations are confirmed for non-urban regions (Figure 12).[9] When comparing the graphs with high dig-skills and non-dig skills (see top left and bottom right), we see a greater number of blue regions in the former and red regions in the latter. In addition, as we move towards the graphs that represent the greater intensity of digital skills, we notice that the share of resilient regions (coloured blue) increases. Conversely, the situation worsens if we take the reverse route in the shape of a "Z", starting at the top-left to the top-right, then to the bottom-left and ending at the bottom-right.

[9] Figure 14 helps to support this affirmation.

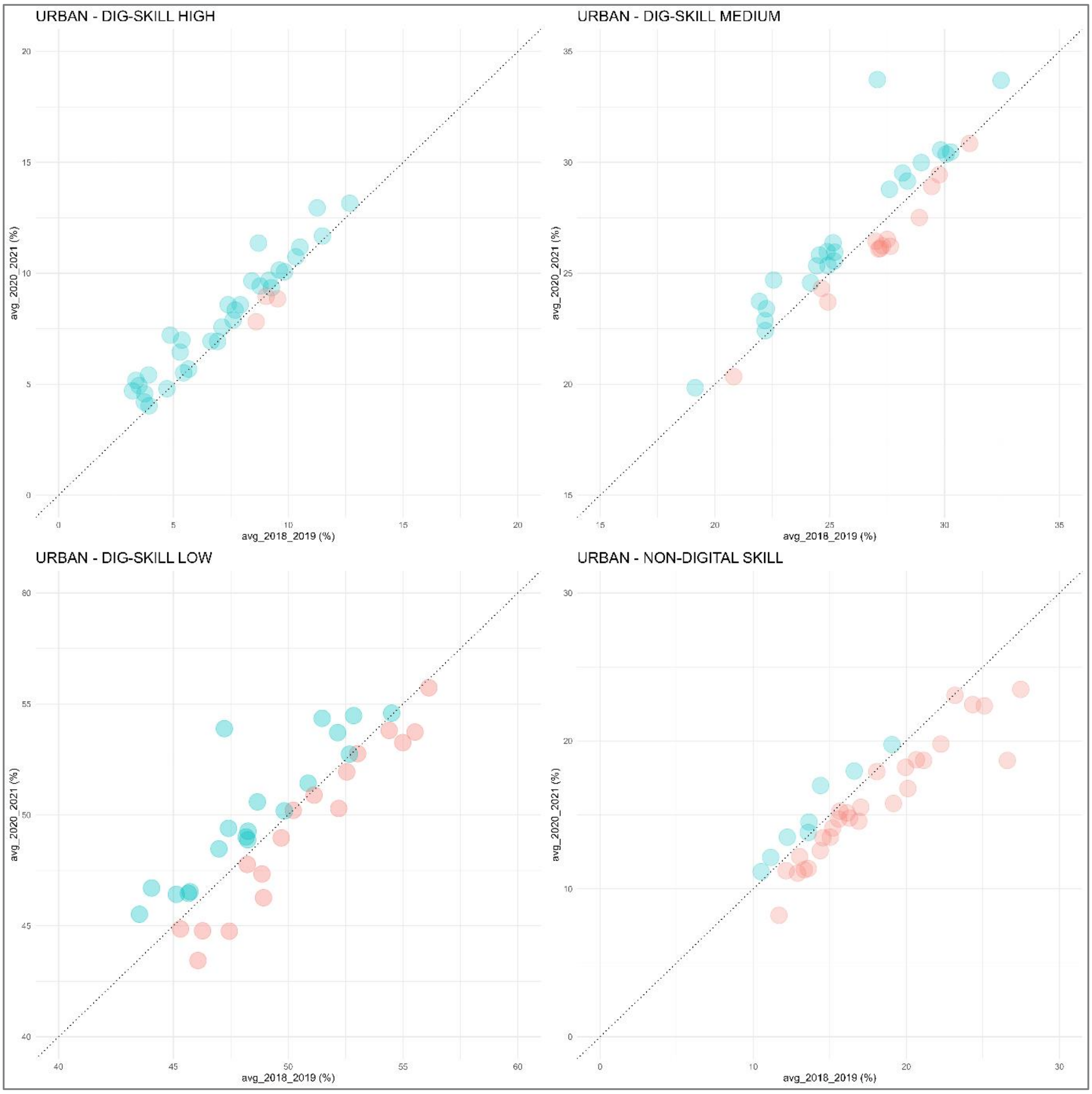
Figure 12 - Comparative position before and during the pandemic – employment in non-urban regions by digital skills intensity



Source: Authors' elaborations based on LFS and ESCO.

The graphs in Figure 13 show the resilience results for urban regions. As we can see, the number of NUT2 regions classified as urban is much lower than that of non-urban regions.

Figure 13 - Comparative position before and during the pandemic – employment in urban regions by digital skills intensity



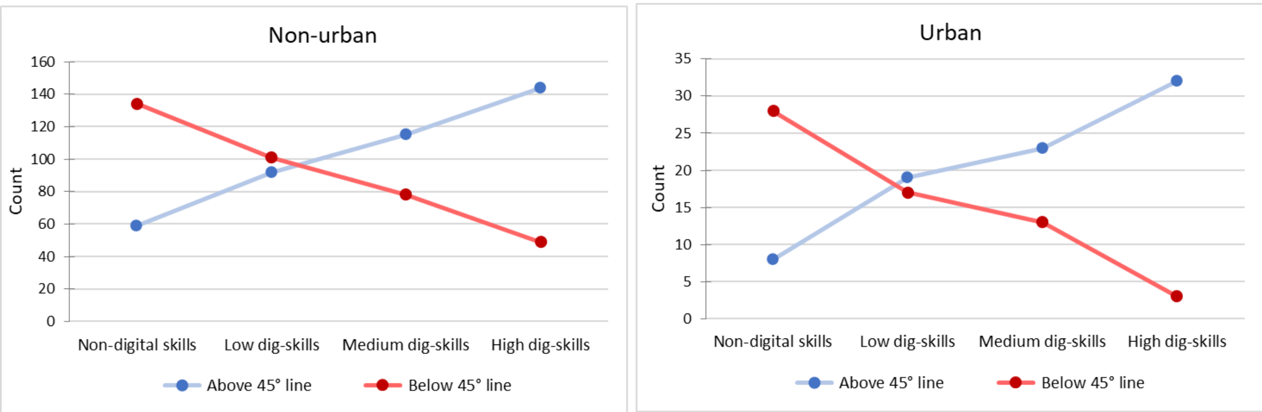
Source: Authors' elaborations based on LFS and ESCO.

Our hypothesis is also confirmed in urban regions (Figure 13). Regions are more resilient as we move up the scale of the intensity of digital skills. In only three regions (less than 10%), the share of jobs with high digital skills intensity reduced during the pandemic. This percentage increases as the intensity of digital skills decreases and reaches around 50% of the regions in the low dig-skills group and 75% in the non-digital skills group.

Figure 13 also shows that more urban regions turn blue as we go along the reverse route of the letter "Z", that is, from the non-digital skills graphs towards the high dig-skills intensity. This means that a greater number of regions showed a positive change in the share of occupations compared to before and during the pandemic.

To summarise and make it easier to visualise the distribution of regions above or below the 45-degree line, we have drawn up Figure 14. It simplifies the two previous figures (Figures 12 and 13) by proving that the count of regions above the 45° line grows as the digital skills intensity of the occupation increases (blue line on the graph) for both urban and non-urban regions. Moreover, the opposite is true: the count of regions below the 45° line (red line) falls as the intensity of digital occupation skills increases.

Figure 14 - Average employment performance by digital skills intensity by region

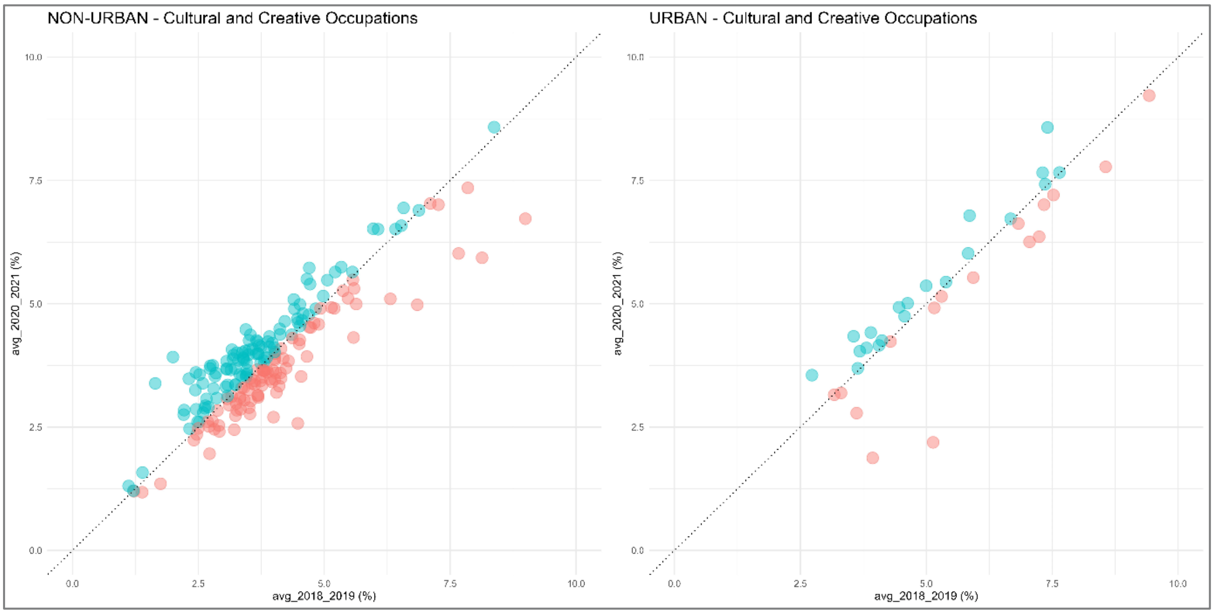


Source: Authors' elaborations based on LFS and ESCO.

To complement the resilience assessment, we also propose to analyse CCOs within non-urban and urban regions. We want to know if the greater participation of CCOs in the regions has also influenced the resilience of the regions during the pandemic.

Figure 15 shows the comparative position of non-urban regions on the left and urban regions on the right, considering only the CCO share. In this exercise, the distribution of regions above and below the 45-degree line is similar in both urban and non-urban regions. Therefore, the share of CCOs increased (or decreased) during the pandemic in practically half of the regions[10], whether urban or non-urban. Therefore, we cannot generally confirm that a higher share of CCOs has made regions more resilient during the pandemic.

Figure 15 - Comparative position before and during the pandemic – employment in CCO in non-urban and urban regions



Source: Authors' elaborations based on LFS and ESCO.

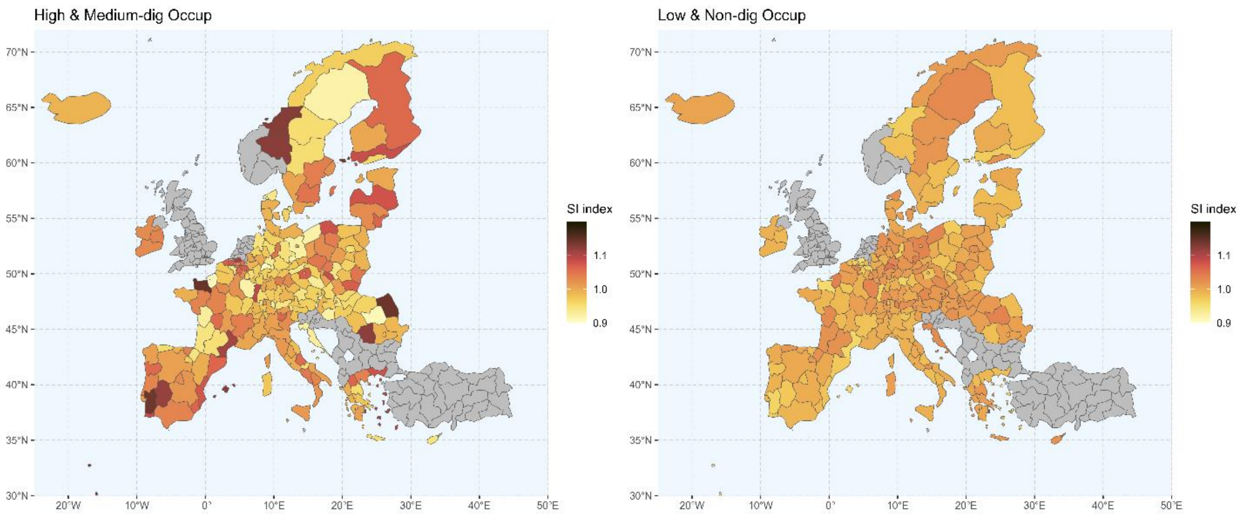
Thus, the resilience of the regions in terms of the share of CCOs in total employment is different between the regions, with some regions having a more significant share than others but with no definitive pattern.

[10] In total, in non-urban regions there are 107 regions above the 45° line and 92 below; and in urban regions there are 20 above 45° line and 16 below the line.

To better qualify the regions and their resilience, we calculated the Sensitivity Indicator during the pandemic. Many articles assessing the resilience of regions to external shocks (such as the 2008 global financial crisis) use mainly two indicators: sensitivity index (SI), a proxy for the resistance of a region to a shock; and response index (RI), a proxy for its capacity to recover from a shock (Faggian *et al.,* 2018; Filippetti *et al.,* 2020; Martin, 2012). SI is calculated considering the period of the shock concerning a previous period (Faggian *et al.,* 2018). While we do not yet have data available for all the NUTS 2-digit regions to calculate the RI index, we can already calculate the SI. The following maps provide a graphical representation of the SI index across different levels of our digital classification.

In Figure 16, we have aggregated the high and medium dig-skills intensity occupations in the map on the left and low and non-digital skills occupations in the map on the right. The SI scores for each occupation group by skills intensity and region can be found in Appendix C.

Figure 16 - Resilience: Sensitivity Index for occupations by digital skills intensity



Source: Authors' elaborations based on LFS and ESCO.

Looking at Figure 16, a few observations come to light. Firstly, the map on the left (high and medium dig-skills) has a larger dispersion of values, represented by the higher diversity of colours.

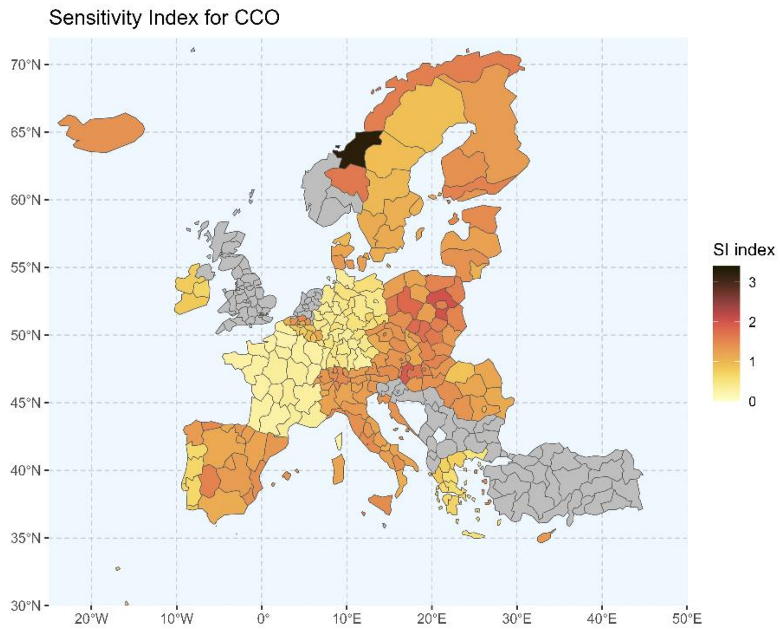
Secondly, on this same map, there are regions in several countries with high SI, that is, good shock resistance capacity. This means that, while some regions may have been less affected by the COVID-19 shock, possibly because of their reliance on digital skills, the same kind of occupations in other areas suffered substantially.

Thirdly, on the right map (low and non-dig skills), the colours are very close, indicating that the SI performance was very similar in all regions, mainly with intermediate values in most regions.

Finally, when comparing both maps, we can see that there are more cases of regions with high SI index when considering high and medium dig-skills occupations (left map). This could suggest that high and medium dig-skills occupations had a more positive influence on the resilience of the regions than the presence of occupations with low and non-dig skills.

Next, we calculated the Sensitivity Index for CCOs only. It is interesting to note in Figure 17 a regional breakdown based on countries' borders. The SI scores for CCOs in each region are also available in Appendix C.

Figure 17 - Resilience: Sensitivity Index for CCO



Source: Authors' elaborations based on LFS and ESCO.

The SI reflects the ability of a region to perform relatively better (or worse) compared to the average during a recession (Filippetti *et al.,* 2020). In this sense, we can make relative regional comparisons. On the one hand, regions in France, Germany, Greece and Portugal do not show good resilience due to their lower SI index values (Figure 17). On the other hand, most of the other countries, especially regions of Poland and Norway, along with Spain, Finland, Iceland and Hungary, showed better resilience to the COVID-19 pandemic.

This more apparent division of the SI for CCO by country may indicate that national policies to tackle the pandemic that has affected CCOs have had a more successful effect in some countries, and so there is not as much inequality within a country, but it is more evident between countries.

4.5. Digital market capabilities across European regions

In this section, we exploit the evolutionary perspective on regional resilience to study the role played by the ability of regions to develop digital products. We intend to assess the capabilities related to digital product development evidenced through trademark classes. In this way, we can bring more elements to building the picture of the resilience of the regions because, as Boschma (2015) said, regions are collections of individuals, organisations, industries, networks and institutions that, when combined, can exhibit different resilience processes and path dependence trajectories.

To begin, we present the scenario of trademark classes in recent years and then present indicators of resilience according to the structure drawn up in the previous sections.

4.5.1. Digital and non-digital trademarks in non-urban regions in the EU

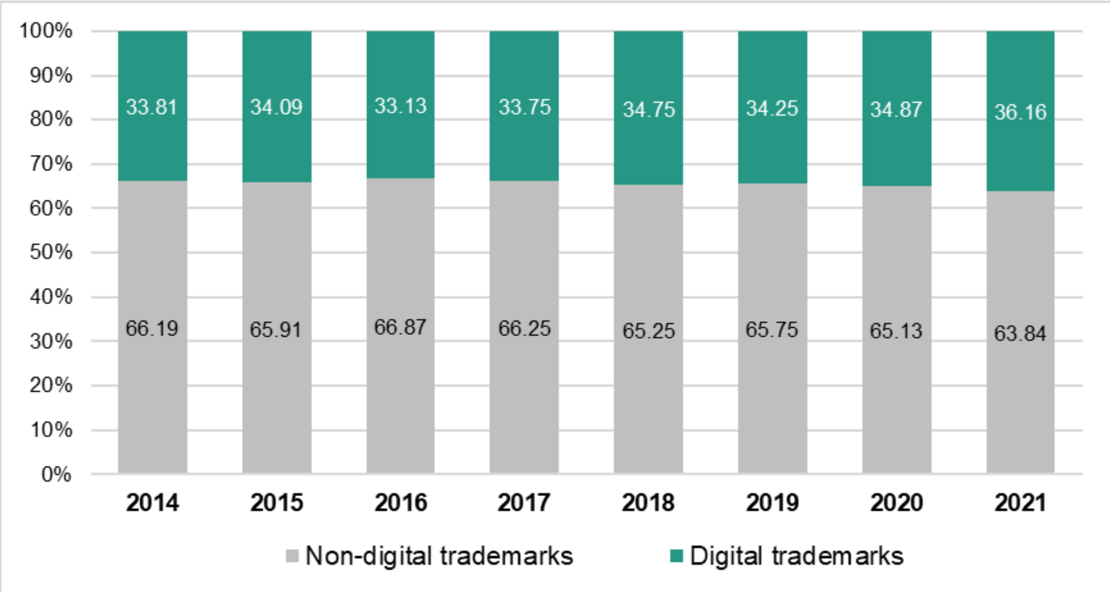
As we saw in Section 3.2.3, of 45 Nice trademark classes, six classes are classified as digital, identified by ICT-related keywords in the descriptions of goods and services (Daiko *et al.,* 2017). The following figures are based on this classification.

Remember that a single trademark application can mention more than one Nice class related to the purpose of the product or service. We counted all the classes indicated in an application, and no fractional counting was applied. Thus, the percentage share of trademark applications (digital and non-digital) was calculated in relation to the total number of Nice classes indicated in applications during the period analysed.

Figure 18 illustrates the share of digital and non-digital trademark classes between 2014 and 2021. Digital trademark classes (or simply "digital trademarks") represent around a third of all trademark classes filled in non-urban regions. This share grew by 6.95% between 2014 and 2021 (from 33.81% to 36.16%), with the most significant growth occurring in the two years of the pandemic when there was an increase of 1.91 p.p. (from 34.25% to 36.16% between 2019 and 2021).

Non-digital trademark applications, in turn, represent the remaining two-thirds. Despite the higher percentage, this type of trademark class recorded a drop of 3.55% between 2014 and 2021 (from 66.19% to 63.84%), being more intense during the pandemic years (Figure 18).

Figure 18 - Share of digital and non-digital trademark classes in non-urban regions



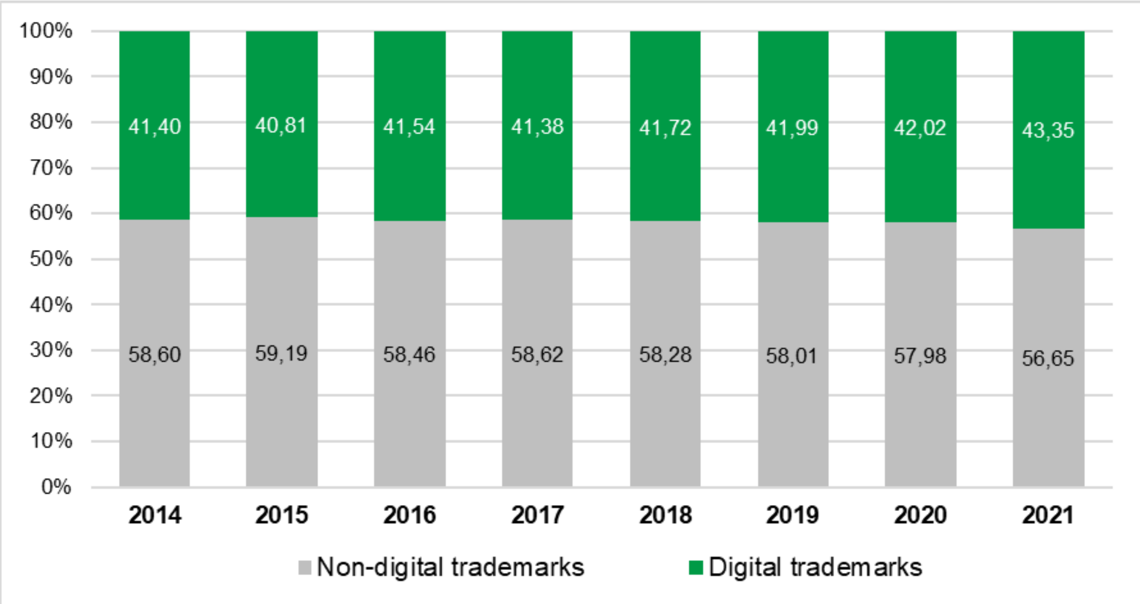
Source: Authors' elaborations based on EUIPO and Daiko et al. (2017).

4.5.2. Digital and non-digital trademarks in urban regions in the EU

Figure 19 shows the distribution of trademark classes between digital and non-digital for EU urban regions. More than 40% of applications refer to digital trademark classes, following a fairly stable percentage over the years analysed. In 2021, digital trademarks classes accounted for 43.35% of total classes filled, the highest percentage of the period. As in non-urban regions, the relative share of digital trademark classes increased in the years of the pandemic, especially in 2021.

Until 2020, there was a minimal annual change in the relative distribution, generally close to 0.5 p.p. or less. However, in 2021, the digital classes increased their relative share compared to the non-digital classes by 1.33 percentage points, the biggest annual change of the period.

Figure 19 - Share of digital and non-digital trademark classes in urban regions



Source: Authors' elaborations based on EUIPO and Daiko *et al.* (2017).

One observation stands out when comparing the performance of both types of regions. In urban regions, applications in the non-digital trademark classes fell by the same percentage as in non-urban regions (around 3%) between 2014 and 2021. However, the percentage of applications of digital trademarks increased more in non-urban regions than in urban regions (6.95% versus 4.71%, respectively) over the same period, with most of this increase occurring during the years of the pandemic.

The possibility of country bias is worth mentioning since urban and non-urban regions in different countries could have responded to the pandemic differently based on national policy support programs.

4.6. Resilience of regions during the pandemic in terms of digital market capabilities

To complement the analysis of the socio-economic resilience of regions during the pandemic, we now focus on the capabilities related to digital product development, also using an evolutionary perspective on regional resilience. We use the information from the trademark applications class and analyse the performance of the regions in the years immediately preceding (2018-2019) and the specific years of the pandemic (2020 and 2021).

In the same way as previously presented (in Section 4.4), the following graphs indicate the position of the regions (NUTS 2 digits) in the period before and during the pandemic. The x-axis indicates the 2018-2019 average (pre-pandemic) of the total number of trademark classes per region. The y-axis indicates the 2020-2021 average (during the pandemic) of the same variable.

When a region is located above the 45-degree line, it indicates that it managed to increase its trademark applications during the pandemic (shown in blue) compared to the pre-pandemic period. When the region is positioned below the 45-degree line, it means there was a reduction in applications during the pandemic (shown in red). Therefore, more resilient regions during the years of the pandemic are identified in blue, while less resilient regions are in red.

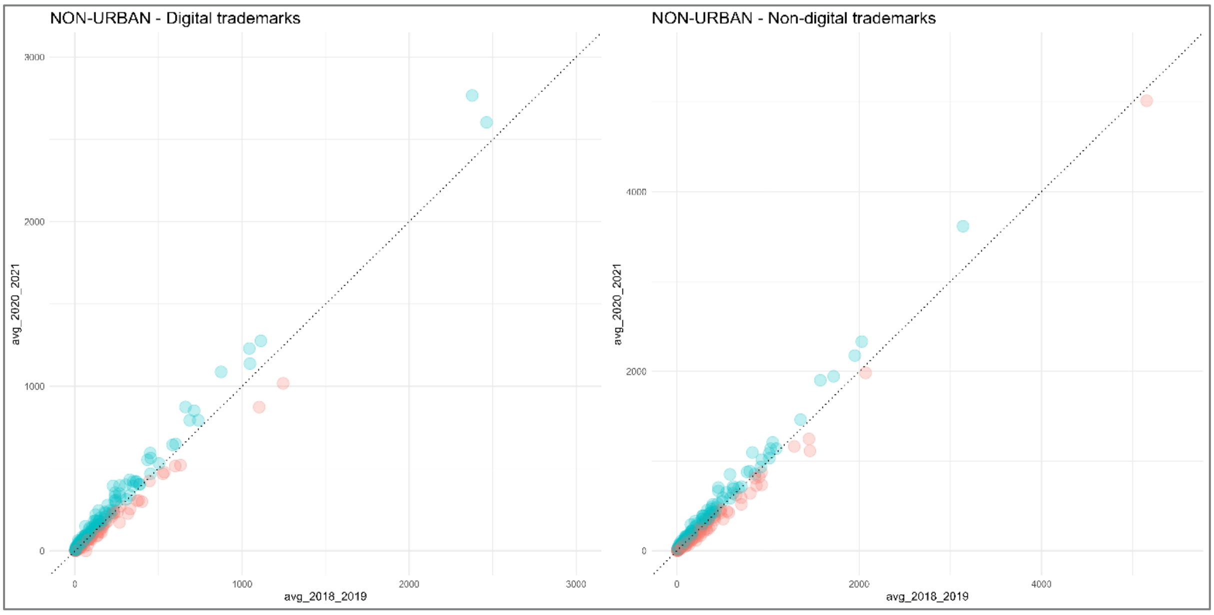
In the face of the shock caused by the pandemic and social restriction measures, industries and individuals have had to reinvent new ways of digitally offering goods and services. Such new ways can be captured with the emergence of new digital markets through trademark applications. Therefore, our hypothesis is that more digital classes of trademarks have emerged during the pandemic, strengthening the resilience of regions.

The result for non-urban regions is shown in Figure 20. On the left, we have the analysis for digital trademark classes; on the right, we have results for non-digital trademark classes.

At first glance, there appear to be more blue regions in the two graphs. Moreover, this impression is confirmed. Around two-thirds of non-urban regions with digital trademarks are above the 45-degree line (coloured blue), while only one-third are below it. As for non-digital trademarks, 59% of the regions are above the 45-degree line, while 41% are shown in red.

As the analysis is hampered by the strong overlapping of regions in the lower part near the 45-degree line, we seek a way to provide more accurate information. For that, we subdivided the sample into two graphs to improve the visualisation of the overlapping regions (see Figure 21).

Figure 20 - Comparative position before and during the pandemic – Digital and Non-digital trademark classes in non-urban regions

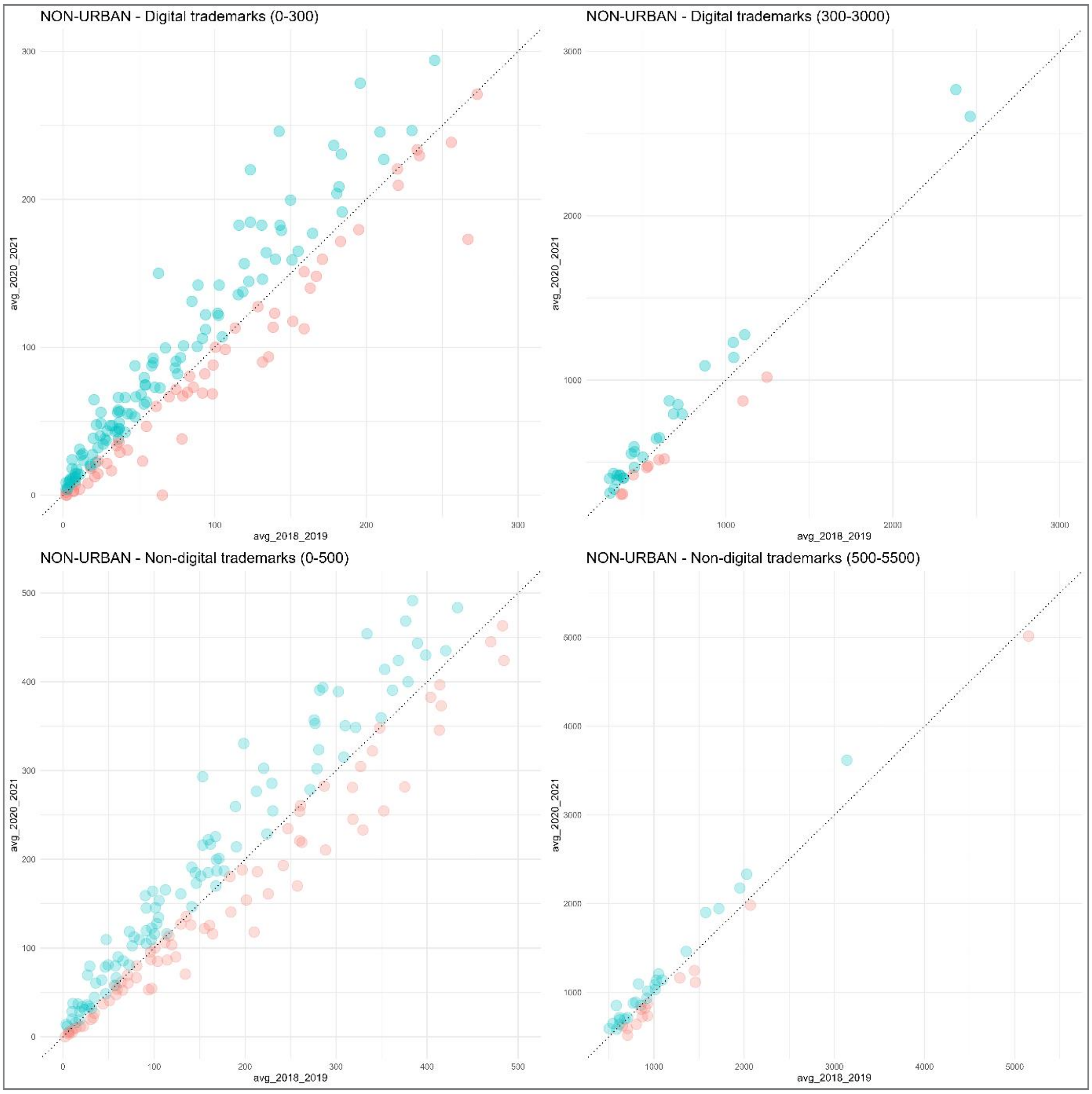


Source: Authors' elaborations based on EUIPO and Daiko *et al.* (2017).

Figure 21 shows the same information as Figure 20 but is divided into two graphs with different scales. The top two graphs show digital trademarks, and the bottom two show non-digital trademarks. The top-left graph shows the non-urban regions with digital trademark class applications ranging from 0 to 300 applications, and the top-right graph shows the rest of the regions with more than 300 applications. The bottom-left graph shows the applications between 0 and 500 of the non-urban regions in non-digital trademark classes, and the bottom-right graph shows the regions with applications above 500.

Here, it becomes clearer that, as expected, trademark applications in digital classes went together with stronger resilience to the shock of the pandemic. This can be said because more than half of the regions are identified in blue – precisely, 68% of non-urban regions. In other words, the majority of non-urban regions that filed trademarks in digital classes have managed to maintain or increase the flow of applications during the years of the pandemic.

Figure 21 - Extension of the comparative position before and during the pandemic for digital and non-digital trademark classes in non-urban regions

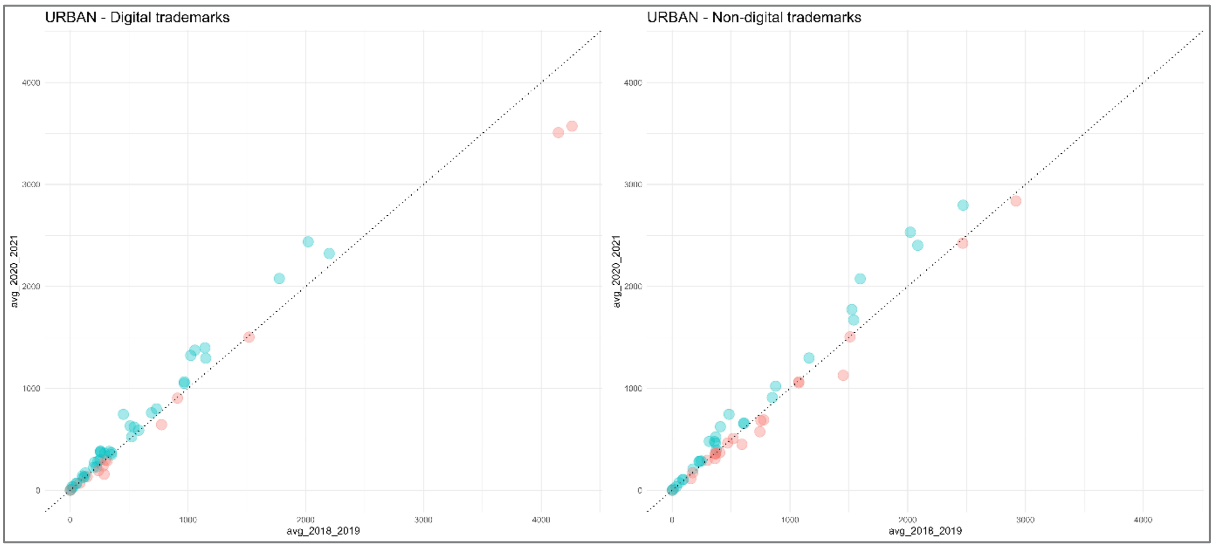


Source: Authors' elaborations based on EUIPO and Daiko *et al.* (2017). Note: same information as Figure 19 but changed axes.

Even in the case of non-digital trademark classes, a large proportion of regions appear in blue (around 59% of them) – see the graphs at the bottom of Figure 21. In this case, other forms of products and services not involving digital technologies have also performed relatively well during the pandemic, but to a lesser extent than digital forms.

Figures 22 and 23 show the results for urban regions. In Figure 22, the graph on the left shows digital, while the graph on the right shows non-digital trademark classes. There is a greater tendency for regions to be located above the 45-degree line (i.e., in blue), indicating a positive variation in the average number of trademark applications in 2020-2021 compared to 2018-2019. More than 70% of urban regions with a digital trademark are blue, while for urban regions with a non-digital trademark, blue represents 54% of regions.

Figure 22 - Comparative position before and during the pandemic for digital and non-digital trademark classes in urban region



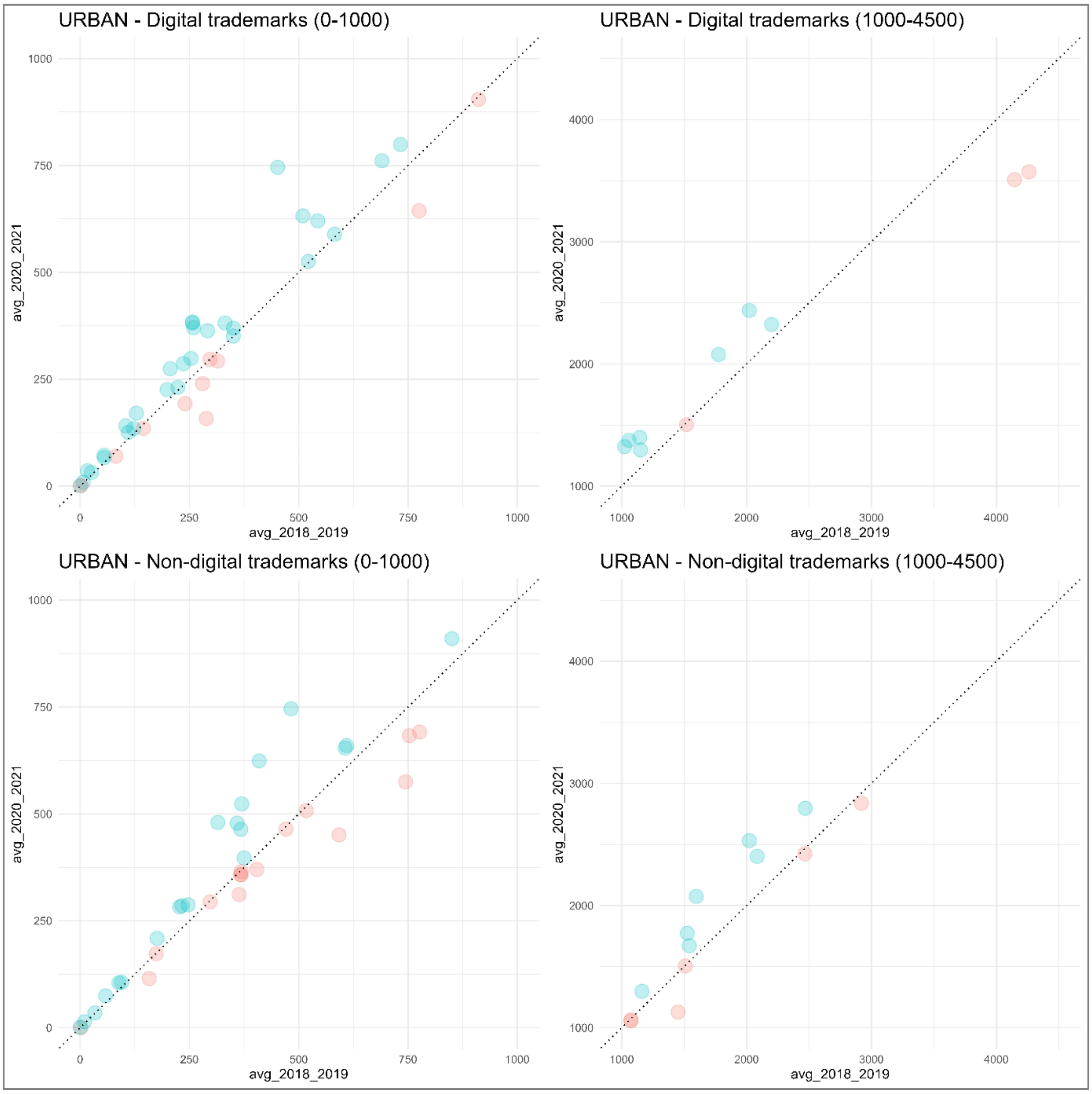
Source: Authors' elaborations based on EUIPO and Daiko *et al.* (2017).

Following the same strategy adopted in Section 4.4, we subdivided these graphs into two parts to better visualise the overlapping regions in the lower portion. This subdivision is shown in Figure 23.

The graphs in Figure 23 make it clearer to see the difference between digital and non-digital trademark classes in urban regions. We note that in the two upper graphs representing digital classes, the vast majority of regions proved to be resilient during the pandemic (blue colour). Digital trademarks increased in more than 75% of urban regions during the pandemic.

As for the variation in the fillings of non-digital trademark classes (bottom two graphs), we also noticed that several regions showed resilient behaviour, although not to the same extent as digital trademarks (around 55% of the regions managed to record positive growth).

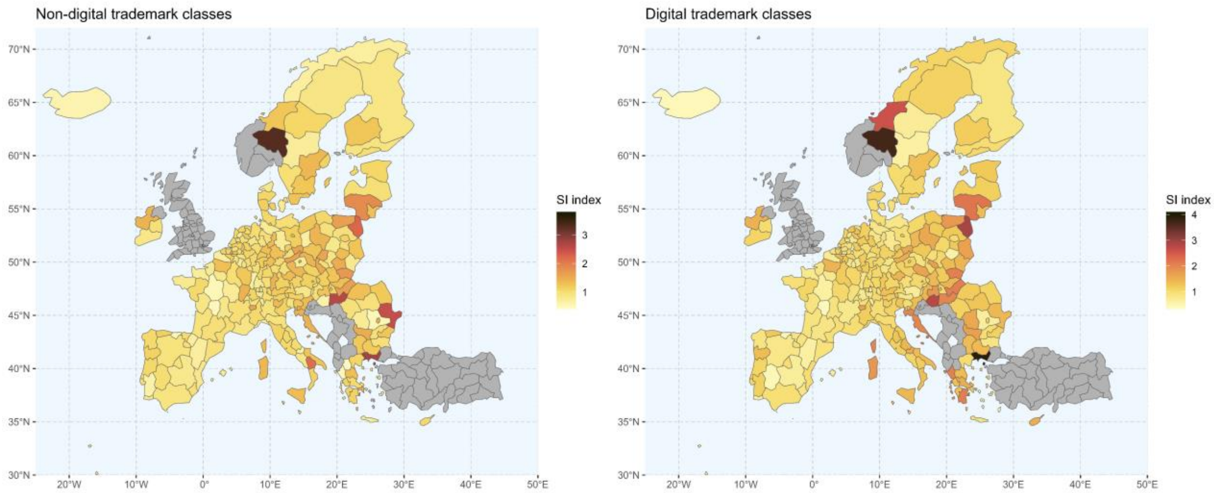
Figure 23 - Extension of the comparative position before and during the pandemic for digital and non-digital trademark classes in urban regions



Source: Authors' elaborations based on EUIPO and Daiko *et al.* (2017). Note: same information as Figure 21 but changed axes.

Below, we assess the resistance of regions in pandemic years using the Sensitivity Index (SI). This indicator was calculated in the same way as presented in Section 3.3.2. In this case, we are considering trademark applications in digital classes (map on the right in Figure 24) and applications in non-digital classes (map on the left in Figure 24). The SI score for trademark classes in all regions can be found in Appendix D.

Figure 24 - Resilience: Sensitivity Index during the pandemic for digital and non-digital trademark classes



Source: Authors' elaborations based on EUIPO and Daiko *et al.* (2017).

A few observations can be drawn from the maps.

Firstly, unlike occupations, only a few European regions stand out when we look at trademarks.

Secondly, in general, the resilience indicator (SI) shows that some regions in Eastern Europe perform better than those in the Western part of the continent.

Thirdly, most regions have a relatively similar SI for the digital and non-digital trademark classes.

Fourthly, the regions with the best SI scores (represented by the stronger colours) are spread across several countries. Regarding digital trademark classes, some regions in Norway, Greece, Hungary and Lithuania stand out.

So, in general terms, the indicators analysed show that entry into new digital goods and services markets benefited the regions in the process of resisting the shock. However, this does not mean new entry into traditional or non-digital goods and services markets had no positive effect. In general, both types of trademarks helped regions be more resilient, with new digital goods and services having more widespread growth in more regions.

4.7. Potential for recovery based on regional relatedness

According to Boschma (2015), history is a key input to comprehending regional resilience in the sense that the elements that compose the regional structure – such as pre-existing industries, networks and institutional elements – are crucial to evaluating the possible paths to growth or recovery.

In other words, pre-existing structures in a region provide opportunities but also set limits to the process of adaptation and adaptability (Grabher, 1993), common concepts adopted by evolutionary theory regarding resilience. Adaptation refers to changes within preconceived paths, while adaptability deals with developing new paths.

To suggest elements on which urban and non-urban regions can anchor themselves to promote their recovery after the pandemic, we will use the methodology proposed by evolutionary economic geography to identify the structure of networks and the possible links that can be stimulated from the existing network structure in the region. In this context, they could be seen as potential ways for regions to adapt and recover.

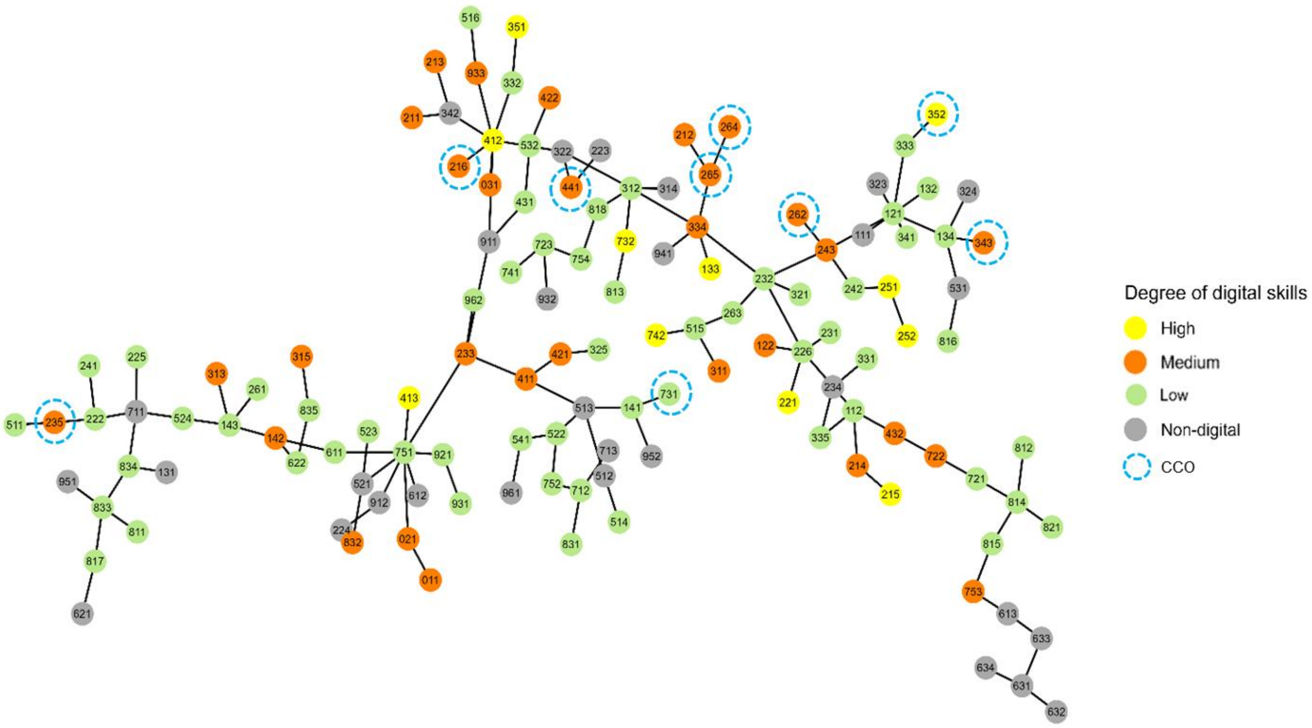
A network connects two occupations that appear together in the same region based on relatedness. When two occupations are linked, there are indications that they have characteristics (skills, knowledge and tasks) that contribute to each other's existence. In this way, it is possible to identify diversification possibilities based on the position and connections of occupations in the network space.

For our analysis, we also use the concept and methodology of relatedness in order to pinpoint elements – among the high-intensity occupations of digital skills and/or among digital trademark classes – that are more related to those already existing in the region and that can more easily emerge in urban and non-urban regions to help in the post-pandemic recovery process. We calculated relatedness and relatedness density using the EconGeo package on R software (Balland, 2023).

4.7.1. Potential for recovery based on digital skills

Figure 25 shows the network structure of occupations by digital skills intensity in non-urban regions. The structure was identified in the years of the pandemic (2020-2021). We believe that from the scenario existing in this period, we can recognise the possibilities for promoting regional recovery by using existing local capacities, which can open up paths for new combinations and diversification in the long term.

Figure 25 - Occupation space by digital skills (2020-2021) – non-urban regions



Source: Authors' elaborations.

In the occupation space in Figure 25, each node in the network represents one of the 130 ISCO 3-digit occupations. The colours indicate occupations by their digital skills' intensity (high, medium, low, or non-digital skills), and dashed blue circles emphasise the CCOs. We followed Hidalgo *et al.* (2007) and applied a max spanning tree (MST) network using Pedersen (2022).[11]

[11] We use the 'ggraph' package and 'lgl' layout in the R software elaborated by Pedersen (2022).

In non-urban regions, high digital skills intensity occupations (yellow) are not in central positions but are located in dense clusters of occupations. Only occupation 412 - Secretaries represent a central link in a fairly diverse cluster (in the top central area).

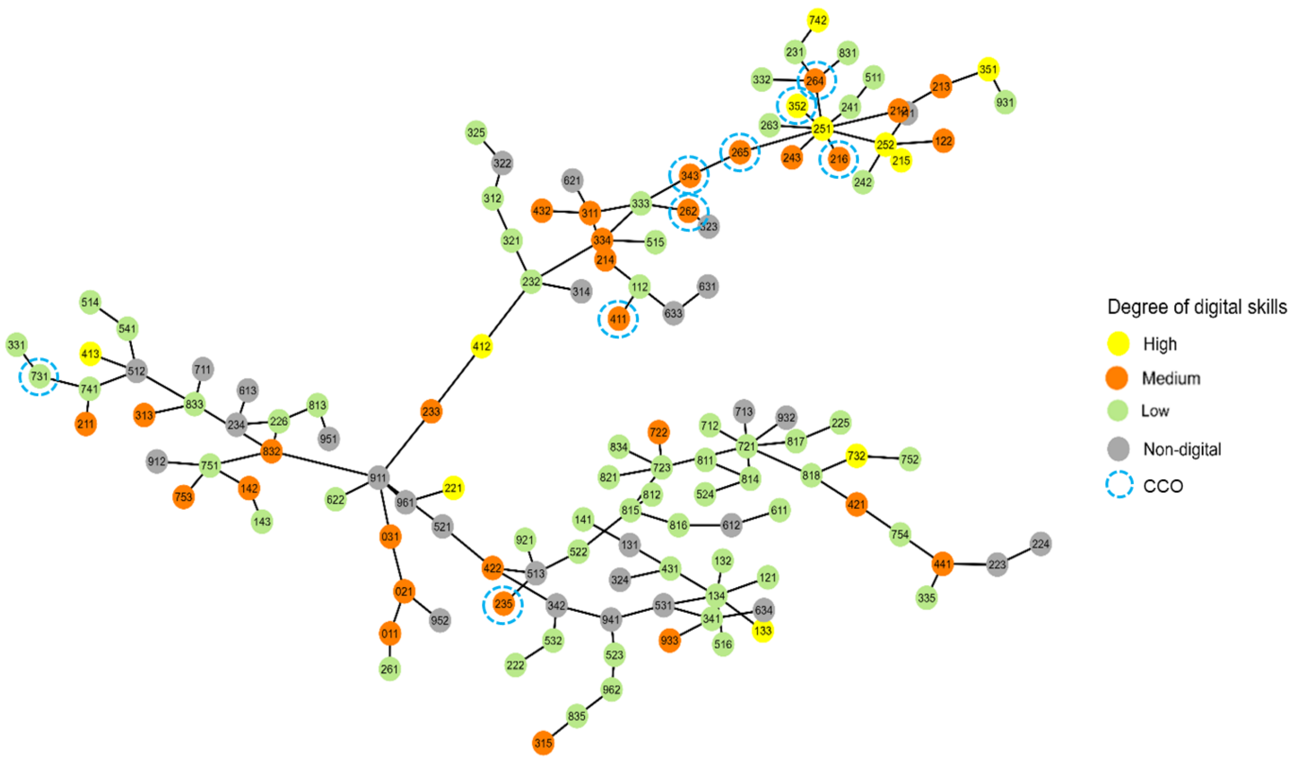
Occupations with medium digital skills intensity (orange) and low digital skills intensity (green), on the other hand, are widely distributed across the network, suggesting that they could be key elements for regional recovery, attracting other occupations that are located close to them.

We also noticed that CCOs 216, 262, 264 and 265 (in the upper central portion) are part of a group linked to medium and high digital skills occupations (respectively, Architects, planners, surveyors and designers; Librarians, archivists and curators; Authors, journalists and linguists; and Creative and performing artists). Thus, they also have the potential to be part of the recovery process in non-urban regions.

Figure 26 presents the occupational space obtained from the structure of jobs in urban regions in the years of the pandemic. The figure shows that high digital skills occupations (yellow) are concentrated in a cluster (top right side) and are mainly linked to other occupations of medium (orange) and low digital skills intensity (green). Few non-digital skills occupations (grey) are part of this cluster. In this case, it may make sense for the recovery of urban regions to follow a path based on occupations with a high intensity of digital skills since they have the potential to pull in other occupations that also demand digital skills existing in the regions.

Interestingly, six of the nine CCOs are located in this same cluster, close to high and medium digital skills occupations (Figure 26). Thus, they could also benefit if the recovery process stimulates jobs with digital skills.

Figure 26 - Occupation space by digital skills (2020-2021) – urban regions



Source: Authors' elaborations.

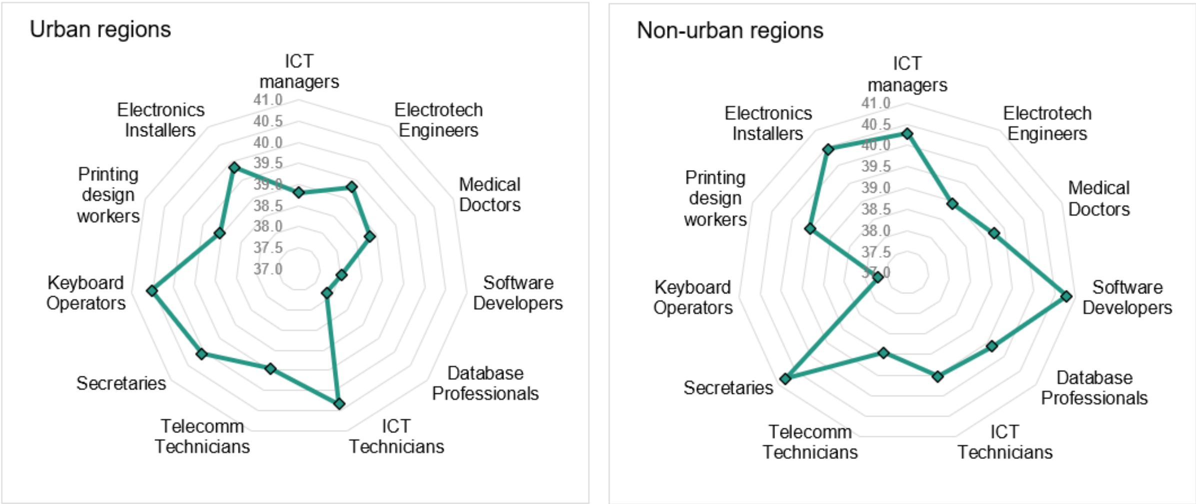
These networks have shown us that there are safer paths to recovery by diversifying into close links that the region already has with related capacities.

We now try to identify which professions, among those with high digital skills, are more closely related to the local structure using relatedness density (RD). Since RD represents the distance between an occupation and the existing occupational structure in a region, we can indicate a likely path for recovery based on the existing resources in the region.

The values of RD range between 0 and 100, as in the graphs presented in Figure 27, where higher values indicate a higher proportion of related occupations in which the region is already specialised.

The webs (or radar) in Figure 27 compare the RD between the 11 occupations classified as high digital skills intensity positioned at the edges. On the left, we display the RD radar for occupations in urban regions, and on the right side is the RD radar for non-urban regions. The higher the RD of an occupation, the greater the chance that it will become part of specialisation in the region or further increase its specialisation if the region already specialises in that.

Figure 27 - Relatedness density for high digital skills occupations (2020-2021) – urban and non-urban regions



Source: Authors' elaborations.

Results in Figure 27, left, show that ICT technicians and keyboard operators are the high dig-skill occupations more related to the local structure in urban regions. This high-relatedness suggests regions can strengthen specializations or acquire a new specialization in these domains more easily compared to other high dig-skill occupations.

For non-urban regions (Figure 27, right), software developers and secretaries are the two high dig-skill occupations most relevant for future diversification opportunities, followed closely by electronics installers and ICT managers. Many software developers live in places with good amenities and work from home, so those regions may be attractive for remote workers who could also help with the regional recovery. Specifically, in the case of secretaries, this is a very generic occupation present in various industries and activities. This may be why it has been listed with a high RD, since they stand out in relation to the total number of occupations in non-urban regions with comparative advantage – which are often not as diverse as urban regions.

4.7.2. Potential paths for recovery based on digital market capabilities

In this section, we explore market diversification opportunities in terms of trademark classes focused on digital classes. In this network structure, two interconnected trademarks indicate that some characteristics (technologies, utility, destination, etc.) contribute to each other's existence. Therefore, new paths are more likely to occur in the direction of closer trademark classes in the network. We calculated the link based on the relatedness measure from the EconGeo package on R software (Balland, 2023).

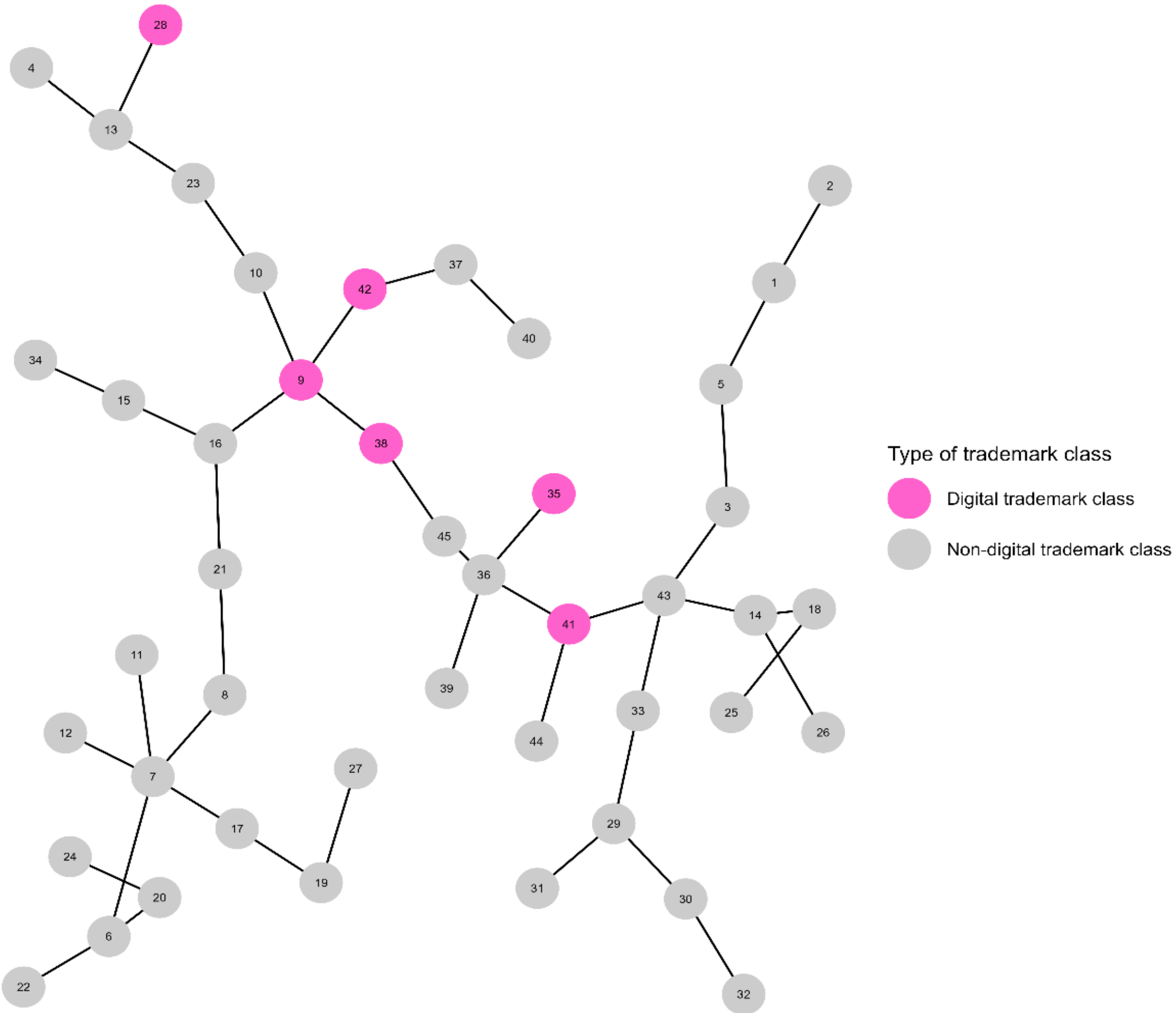
Figure 28 presents the trademark space constructed from the 45 Nice classes in non-urban regions during the pandemic (2020-2021). We also applied a maximum spanning tree to build the network[12], following the Hidalgo *et al.* (2007) approach. Each node in the network represents a Nice class, where digital trademark classes are pink and non-digital classes are grey.

The first observation we can make for non-urban regions (Figure 28) is that most digital trademark classes are central links or leading nodes within the network, that is, operating as facilitators to connect other trademark classes (except for classes 28 and 35). This suggests that digital trademark classes are important for the process of diversification and recovery, as they connect links that would not otherwise be connected.

Class 9, in particular, is a relevant link on the network. This digital trademark class includes equipment for scientific research, photographic, audio-visual, and instruments for recording sound, images or data. It connects practically all the other classes and is directly linked to two other digital classes (38 and 42). In this sense, a possible path to recovery after the pandemic could be based on the digital product development encompassed in this class in order to take advantage of the region's previous capabilities.

[12] We are using 'ggraph' package and 'lgl' layout in the R software elaborated by Pedersen (2022).

Figure 28 - Market space by trademark classes (2020-2021) – non-urban regions

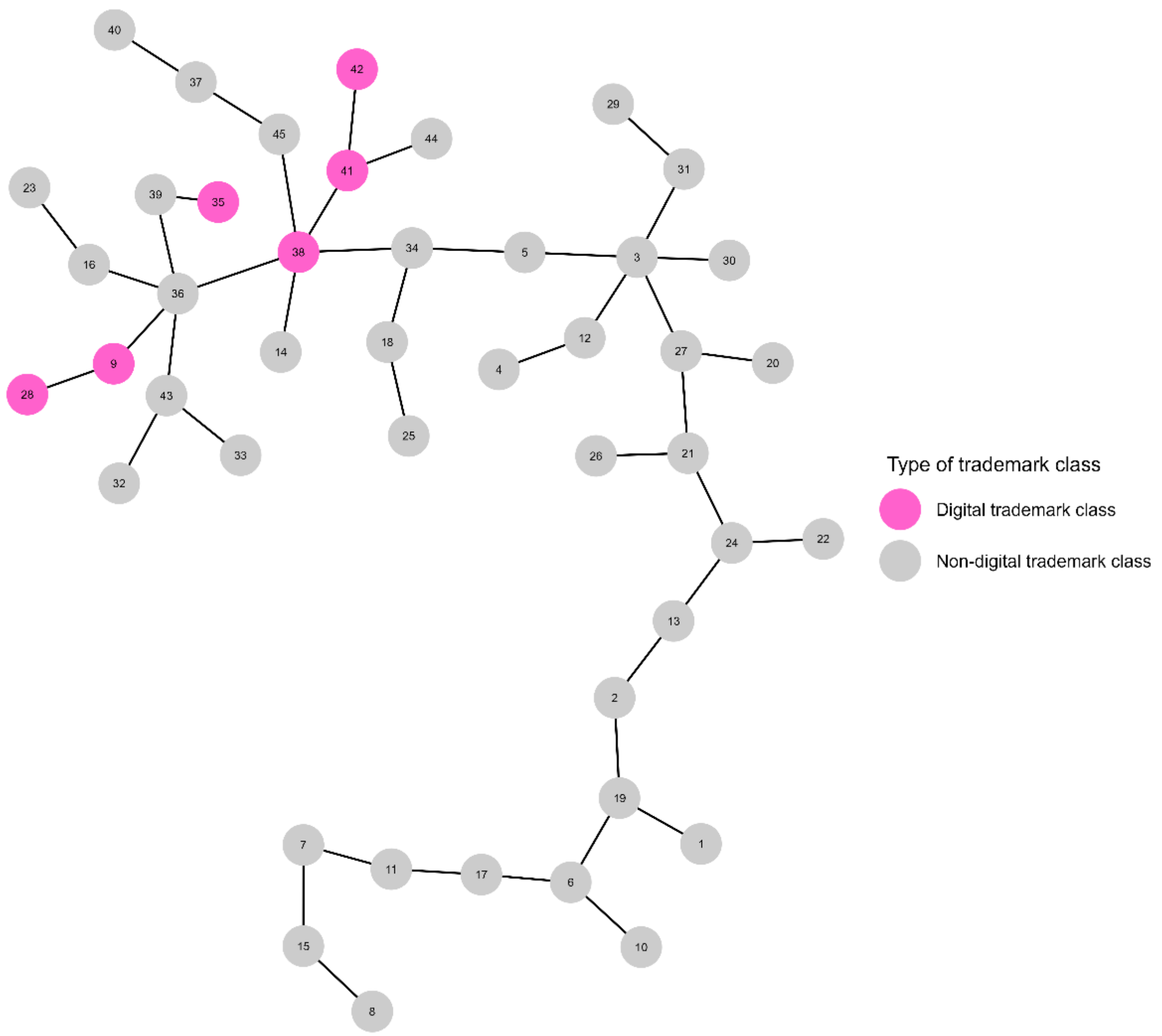


Source: Authors' elaborations.

Turning now to urban regions (Figure 29), we see that the possibilities for establishing more solid development paths based on the region's digital market structure are centred on classes 38 (telecommunications) and 41 (education; training; entertainment; sporting and cultural activities). These two digital classes are central, especially class 38, and are linked to other classes, having the potential to stimulate the development of other markets (digital and non-digital) more easily.

The other digital classes are positioned at the network's edge (especially 26, 9 and 35) but are still part of a dense cluster with other classes of non-digital trademarks around them. They can, therefore, also benefit from being stimulated by the development of some non-digital markets.

Figure 29 - Market space by trademark classes (2020-21) – urban regions

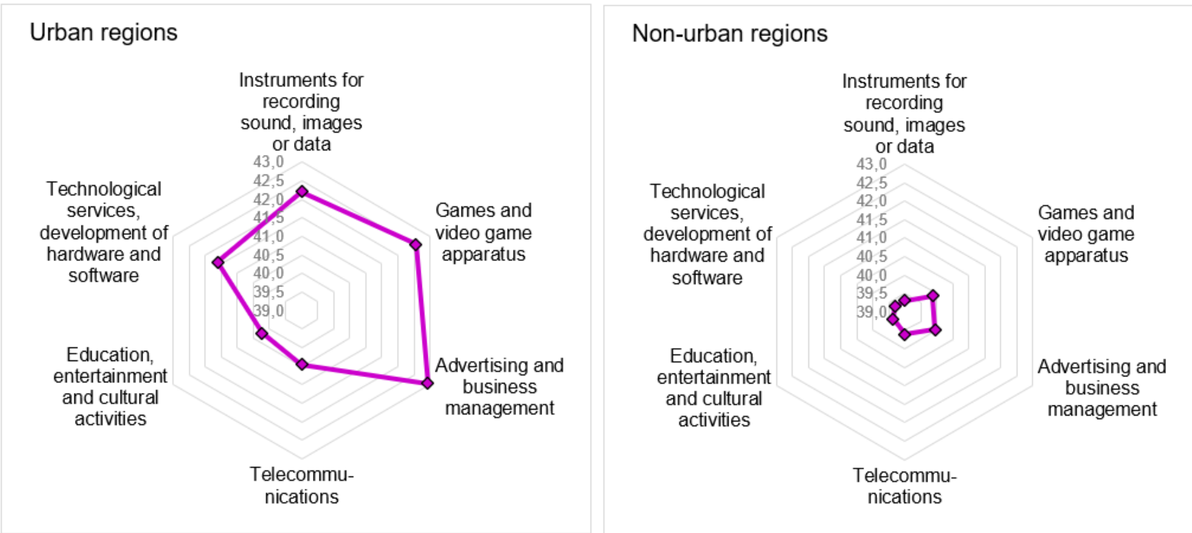


Source: Authors' elaborations.

To link the market space with the economic structure of the regions, we calculated the relatedness density (RD) for digital trademark classes. The following figures show which digital trademark classes are most likely to emerge in a region and make it specialised in that market.

Figure 30 displays the RD radar calculated for the six digital trademark classes. As stated before, the higher the RD of a digital class, the greater the chance the regions become specialized in this class or even further increase its specialisation.

Figure 30 - Relatedness density for digital trademark classes (2020-2021) – urban and non-urban regions



Source: Authors' elaborations.

In urban regions (Figure 30, left), three digital classes are most prominent: advertising and business management; games and video game apparatus; and instruments for recording sound, images or data.

The high RD of these three classes signals that they may be the safest possible specialisation paths for urban regions to use to recover from the pandemic. Since they are already strongly associated with the local structure, urban regions can take advantage of this similarity to launch new combinations and access new markets.

On the other hand, in non-urban regions (Figure 30, right), all the digital classes of trademarks have a similar RD (close to 39), i.e., none of them stand out. In this case, an alternative is to look for the development of classes with high RD linked to them, which could consequently lead to the formation of elements that open up solid development paths towards digital markets.

Finally, this result indicates that regional development or recovery based on digital markets is more viable in urban regions than non-urban ones. This might be linked to the accessibility of support for obtaining trademarks, as most of the related support structures are based in regional capitals. In this sense, regional offices or support organisations for initiatives located in non-urban regions are crucial to promoting the use of this type of intellectual protection in regions far from urban centres.

5. Final remarks

The main objective of this report was to shed some light on the role of digital technologies and the occupational composition of the region in shaping the resilience of non-urban regions, especially in terms of the ability of creative and cultural activities to resist the COVID-19 shock. Recognising that there are other ways to measure resilience through other quantitative approaches but also with qualitative research, especially in cultural and creative activities, we opted for an original quantitative approach, measuring occupational composition via LFS data and markets through trademark applications.

To this end, we combined different contributions across literature on creative and cultural occupations, evolutionary economic geography and the nascent literatures on resilience and the impacts of COVID-19 and performed a descriptive analysis linking digital skills, cultural and creative occupations and digital trademarks and the impact of the COVID-19 pandemic.

Our analysis highlights four main points on the relationship between creative and cultural activities and digital skills in non-urban regions.

First, based on our descriptive evidence, we show that, on average, the shares of digital and creative and cultural occupations have not changed much over time, even though a simple comparison in the distribution suggests that urban regions may, all in all, perform slightly better. While it is important to keep in mind that aggregating information over large and relatively heterogeneous groups of regions (like non-urban regions) may hide some differences, the overall stable distribution of CCOs and digital occupations during a pandemic remains an interesting finding. Interestingly, analysing the distribution of trademarks instead reveals an overall increment in the share of digital trademarks in the years of the pandemic, with the increase being more pronounced in non-urban regions. This trend may suggest an increased exploitation of digital markets for products or services in non-urban areas. More generally, and in line with Tessarin *et al.* (2023b), this finding highlights the possible important role played by trademarks and soft innovation, more generally, outside core urban regions in Europe.

Second, when testing the resilience of occupations and trademarks across different groups based on their reliance on digital technologies, we show how occupations and trademarks which are "more digital" weathered better the COVID-19 shock. For instance, when comparing the share of jobs in the regions in the period before and during the pandemic by the intensity of digital skills, we notice that the number of regions experiencing a growth in employment in the occupation group compared to regions experiencing a decline in employment in the occupation group is higher in the case of high dig-skills occupations, while the opposite holds (more regions experiencing employment contractions) for non-dig skills. We interpret this finding as suggestive of a possible role of digital skills in dampening the shock and making regions more resilient. In fact, based specifically on this descriptive analysis, the differences between urban and non-urban regions appear to be negligible. The comparative analysis of the distribution of digital trademarks over time confirms our findings, in general showing an even clearer pattern linking digital trademarks to resilience.

As an alternative approach to studying resilience, we computed a sensitivity index through which we wanted to capture the sensitivity of a region to the COVID-19 shock and, which connects to our third point. Comparing the maps, we notice that the presence of occupations with high and medium dig-skills had a more positive influence on the resilience of the regions than the presence of occupations with low and non-dig skills in the EU regions. Interestingly, when looking at the map with the sensitivity of cultural and creative occupations, the variation occurs mostly between countries, suggesting a possible role for national-level interventions in influencing the impact of COVID-19 on CCOs.

Lastly, our analysis of the occupation space for non-urban regions indicates that high digital skills intensity occupations may not be leveraged towards diversification – as they are not central in the network. A better choice may be occupations with medium digital skills intensity and even some CCOs, given their relatively central position and connection to resilient medium and high digital skill occupations. Overall, however, the comparison with urban regions suggests more densely populated and urbanised areas are in a better position to leverage digital occupations and CCOs.

We should also stress that our analysis presents some limitations, especially in terms of data. Along with a recurrent problem with the granularity of the data both in terms of occupations as well as in terms of geography, the main limitation is the short-term nature of the analysis. It is still too early to assess the resilience of CCOs and trademarks after the pandemic. This is an important limitation since various countries introduced measures to support incomes and compensate for the effects of lockdowns during the pandemic. This may imply that the full effect of the COVID-19 shock may only be assessed in a couple of years.

A second limitation of our analysis connects to the classification of digital occupations. While the availability of information on the skill set used in various occupations was critical in capturing "how digital" occupations are, we selected reasonable thresholds for defining high-, medium- and low-dig occupations without further robustness checks. Since the category of digital skills is quite new at ESCO, studies are emerging with the aim of identifying digital and non-digital occupations without worrying about calculating the digital intensity of each occupation. In our work, we went further and proposed a subdivision within the category of digital occupations. Given its experimental nature, additional analyses are needed to validate this categorisation. Also, our classification of digital trademarks should be seen as a first attempt. Further research could rely on emerging approaches that use text analysis of the descriptions of goods and services in trademarks (Castaldi and Mendonça, 2022).

Given the above limitations and the highly exploratory nature of our analysis, we are reluctant to translate our analysis into specific policy recommendations. This work should be used as a starting point to investigate in greater detail and in more contextualised ways the implications of exogenous shocks in general and of the COVID-19 pandemic in particular. In these respects, the IN SITU project will provide more specific and tailored evidence within Work Package 3 (Task 3.5).

Our work opens up some avenues for future research. With respect to our methodological choices to assess socio-economic resilience, future research could combine qualitative studies with a quantitative approach covering the European Union. The impact of the pandemic can be assessed comprehensively, including non-traditional forms of employment (such as freelancers, intermittent workers, etc.) and formal employment. Furthermore, the employment conditions of cultural and creative workers are also a key point for understanding resilience and opportunities for recovery from the shock, as the pandemic may have led many workers to change jobs (outside cultural and creative activities) or made digital skills training impossible due to the loss of income during the pandemic.

Another topic that should be further explored is the classification of digital skills intensity by occupation. Our tentative provides a first measure of the importance of digital skills for every ISCO occupation. However, this measure is open to improvements and suggestions for refinement. Future research could also better evaluate groups of occupations with low-, medium- or high digital skills intensity in order to test the relevance of digital occupations in different industries and regions.

Our results could also be a fertile field for new ideas to understand in more detail the elements that explain the performance and resilience of the regions. For instance, one of our results pointed to higher IS scores in several EU regions regarding digital trademarks. This could be an interesting topic for future research to better understand the policies adopted in these regions, as well as the regional capacities present that supported the improved resilience of these regions.

Another research focus could be on digital and non-digital trademarks and the performance of regions specifically to assess further whether there is a country bias. In this case, it can be investigated, for example, whether performance differs significantly in countries that traditionally use this type of intellectual protection and whether this has led to a greater frequency in the application of digital trademarks specifically. Another analysis could provide an institutional investigation and evaluate the need or effectiveness of a widespread regional presence of support institutions for trademark application in non-urban regions with solid potential to advance in digital markets.

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Appendices

Appendix A: Allocation of regions by degree of urbanisation

Eurostat classifies regions at 3-digit NUTS by degree of urbanisation as predominantly urban, intermediate and rural. Since our data is at 2-digit NUTS, we use the distribution of employed persons in each NUTS 3 to classify NUTS 2 regions as predominantly urban or non-urban. Table 3 presents the number of urban and non-urban regions by country allocated according to this methodology.

Table 3 - Countries and numbers of NUTS regions by degree of urbanisation

Country	Urban regions	Non-urban regions
AT	1	8
BE	1	10
BG	3	3
CH	0	7
CY	1	0
CZ	1	7
DE	10	33
DK	1	4
EE	0	1
EL	1	12
ES	15	11
FI	1	4
FR	6	23
HR	0	2
HU	1	7
IE	1	2
IS	0	1
IT	4	20
LI	0	1
LT	1	1
LU	0	1
LV	0	1
MT	1	0
NL	1	0
NO	1	7
PL	5	14
PT	3	6
RO	1	7
SE	2	6
SI	0	2
SK	1	3
Total	**78**	**216**

Source: Authors, based on Eurostat and LFS.

Appendix B: List of non-digital skills occupations

By applying our methodology to classify the digital skills intensity of occupations, some occupations do not even require digital skills to perform their tasks. These occupations were classified in the group called "non-digital occupations" and the list of this group is presented in Table 4.

Table 4 - List of non-digital skills occupations

ISCO 3D code	Description
111	Legislators and Senior Officials
131	Production Managers in Agriculture, Forestry and Fisheries
223	Traditional and Complementary Medicine Professionals
234	Primary School and Early Childhood Teachers
314	Life Science Technicians and Related Associate Professionals
322	Nursing and Midwifery Associate Professionals
323	Traditional and Complementary Medicine Associate Professionals
324	Veterinary Technicians and Assistants
342	Sports and Fitness Workers
512	Cooks
513	Waiters and Bartenders
521	Street and Market Salespersons
531	Childcare Workers and Teachers Aides
612	Animal Producers
613	Mixed Crop and Animal Producers
621	Forestry and Related Workers
711	Building Frame and Related Trades Workers
713	Painters, Building Structure Cleaners and Related Trades Workers
911	Domestic, Hotel and Office Cleaners and Helpers
912	Vehicle, Window, Laundry, and Other Hand Cleaning Workers
932	Manufacturing Labourers
941	Food Preparation Assistants
951	Street and Related Services Workers
952	Street Vendors (excluding Food)
961	Refuse Workers
224	Paramedical Practitioners
631	Subsistence Crop Farmers
632	Subsistence Livestock Farmers
633	Subsistence Mixed Crop and Livestock Farmers
634	Subsistence Fishers, Hunters, Trappers and Gatherers

Source: Authors' elaborations based on ESCO.

Appendix C: Sensitivity Index (SI) score for occupations by digital skills intensity and CCO

The sensitivity index (SI) during the pandemic (Table 5) was calculated using the 2020-2021 average in relation to 2018-1019. We use the share of occupations, separating them by digital skills intensity (High & Medium, and Low & Non-digital skills) and CCO by region in relation to the European Union average in the same period.

Table 5 - Sensitivity Index (SI) scores for regions by degree of digital skills

NUTS 2	SI High & Medium dig-skill	SI Low & Non-dig skill	SI CCO
AT11	0,92037	1,03265	1,43841
AT12	0,96515	1,01488	1,35752
AT13	0,96807	1,01404	1,38740
AT21	0,97073	1,01232	1,30761
AT22	0,96713	1,01401	1,44058
AT31	0,94356	1,02698	1,29927
AT32	0,97272	1,01135	1,42178
AT33	0,94313	1,02472	1,23429
AT34	0,93099	1,03337	1,40603
BE10	0,99155	0,99832	1,08593
BE21	1,11014	0,94966	1,50142
BE22	1,05402	0,98265	1,35387
BE23	1,07108	0,96918	1,34811
BE24	1,03528	0,97423	1,09513
BE25	1,07007	0,98071	1,06266
BE31	1,04138	0,97270	0,81974
BE32	0,93833	1,02868	0,83252
BE33	1,06793	0,96684	0,85923
BE34	1,03081	0,99153	0,96339
BE35	1,05894	0,97272	0,78493
CH01	0,98406	1,00448	1,22421
CH02	0,98746	1,00301	1,34065
CH03	0,94402	1,03047	1,33643
CH04	1,01575	0,97887	1,45463
CH05	0,99536	0,99985	1,47742
CH06	0,97363	1,01063	1,44875
CH07	0,97430	1,01031	1,48530
CY00	0,94513	1,02306	1,30324
CZ01	1,00804	0,98663	1,48943
CZ02	1,06950	0,97608	1,29198
CZ03	0,97551	1,01059	1,13618
CZ04	0,93952	1,02222	1,35682
CZ05	0,96661	1,01395	1,36600
CZ06	0,93146	1,02861	1,43241
CZ07	1,00612	0,99998	1,08721
CZ08	1,08320	0,97073	1,33447
DE11	0,99414	0,99565	0,39823
DE12	1,00349	0,99058	0,50648
DE13	0,95480	1,02146	0,44169

NUTS 2	SI High & Medium dig-skill	SI Low & Non-dig skill	SI CCO
FRB0	1,03491	0,98555	0,31943
FRC1	0,97465	1,01068	0,33099
FRC2	0,96310	1,01551	0,27629
FRD1	1,14310	0,95576	0,29558
FRD2	0,90830	1,03894	0,26511
FRE1	0,97234	1,01167	0,28439
FRE2	0,97351	1,01136	0,22629
FRF1	1,09254	0,96301	0,28669
FRF2	1,02387	0,99290	0,28747
FRF3	0,92081	1,03254	0,27123
FRG0	1,03479	0,98740	0,28627
FRH0	0,99555	1,00233	0,26820
FRI1	0,94495	1,02308	0,27984
FRI2	1,05706	0,98467	0,30908
FRI3	0,92900	1,02799	0,26735
FRJ1	1,10663	0,96002	0,32520
FRJ2	0,94959	1,02308	0,24863
FRK1	1,01309	0,99673	0,34614
FRK2	1,04125	0,97822	0,29244
FRL0	1,00364	0,99629	0,33118
FRM0	1,01664	0,99537	0,23766
FRY1	1,03626	0,99005	0,34014
FRY2	1,07902	0,97597	0,26887
FRY3	0,95464	1,01877	0,30353
FRY4	0,93063	1,02793	0,27429
HR03	0,92857	1,02677	1,37283
HR04	0,96585	1,01402	1,27463
HU11	0,97631	1,00925	1,39917
HU12	0,94417	1,02101	1,49053
HU21	0,96714	1,01342	1,70177
HU22	0,98976	1,00696	1,95216
HU23	0,92223	1,02411	1,29635
HU31	0,95686	1,01575	1,53253
HU32	0,95637	1,01566	1,36385
HU33	0,96766	1,01315	1,42773
IE04	1,02956	0,99423	0,78717
IE05	1,02999	0,99172	0,81283
IE06	1,03537	0,98500	0,69666
IS00	0,99095	1,00510	1,39192

NUTS 2	SI High & Medium dig-skill	SI Low & Non-dig skill	SI CCO
DE14	0,96872	1,01344	0,44448
DE21	0,98870	0,99912	0,28777
DE22	0,98293	1,00634	0,50076
DE23	1,02840	0,98145	0,43857
DE24	0,97677	1,00894	0,53334
DE25	1,04155	0,96289	0,32821
DE26	0,96647	1,01488	0,35447
DE27	0,97229	1,01139	0,35853
DE30	1,00412	0,98866	0,28136
DE40	0,92227	1,03625	0,44624
DE50	0,97353	1,01053	0,73583
DE60	1,00775	0,98329	0,41297
DE71	0,96536	1,01608	0,37554
DE72	0,90585	1,04881	0,55020
DE73	0,93407	1,03173	0,38225
DE80	0,99512	1,00187	0,57789
DE91	1,04496	0,97004	0,50287
DE92	0,95277	1,02298	0,45866
DE93	0,96604	1,01451	0,53264
DE94	0,94502	1,02478	0,41757
DEA1	1,00405	0,99135	0,37690
DEA2	0,98956	0,99932	0,40957
DEA3	0,96136	1,01705	0,35386
DEA4	0,97233	1,01132	0,30528
DEA5	1,00116	0,99430	0,41266
DEB1	0,96730	1,01418	0,37667
DEB2	0,95133	1,02113	1,17072
DEB3	0,96607	1,01497	0,49607
DEC0	0,98168	1,00628	0,51757
DED2	0,99470	1,00030	0,60247
DED4	0,97120	1,01212	0,55118
DED5	0,92035	1,04171	0,71182
DEE0	0,94892	1,02265	0,41238
DEF0	0,99236	1,00079	0,34459
DEG0	0,95690	1,01936	0,52558
DK01	0,94369	1,02845	1,21663
DK02	0,96357	1,01492	1,24364
DK03	0,99007	1,00436	1,30857
DK04	0,99476	1,00134	1,20438
DK05	0,93994	1,02462	0,98537
EE00	1,00134	1,00059	1,45838
EL30	0,97169	1,01160	0,64098
EL41	1,10460	0,96298	1,42333
EL42	1,10194	0,96821	0,51989
EL43	0,95407	1,01746	0,52159
EL51	1,07831	0,98098	0,51295
EL52	1,03773	0,98816	0,75516
EL53	1,06302	0,98412	0,73808
EL54	0,99737	1,00393	0,83265
EL61	0,95505	1,01712	0,59193
EL62	0,99219	1,00572	0,71158

NUTS 2	SI High & Medium dig-skill	SI Low & Non-dig skill	SI CCO
ITC1	1,00023	0,99922	1,23202
ITC2	1,00330	1,00013	1,11489
ITC3	1,01547	0,99401	1,41400
ITC4	1,01140	0,99067	1,20445
ITF1	1,05677	0,98040	1,22286
ITF2	0,94922	1,02076	1,07039
ITF3	1,04478	0,98196	1,26668
ITF4	1,00450	0,99895	1,20356
ITF5	1,03369	0,98897	1,40394
ITF6	1,01889	0,99513	1,09134
ITG1	1,01607	0,99417	1,44991
ITG2	0,97389	1,01137	1,18009
ITH1	1,01348	0,99354	1,30926
ITH2	1,05970	0,97562	1,19934
ITH3	1,02801	0,98788	1,27511
ITH4	0,98016	1,00761	1,34494
ITH5	1,01178	0,99258	1,29155
ITI1	1,01608	0,99284	1,42389
ITI2	1,00347	0,99926	1,33862
ITI3	0,98228	1,00657	1,20346
ITI4	0,99830	0,99720	1,45035
LI00	0,91382	1,06071	0,88002
LT01	1,06390	0,97081	1,07048
LT02	1,02881	0,99460	1,39835
LU00	0,95693	1,01908	0,88328
LV00	1,07790	0,98331	1,22820
NL00	1,02119	0,98723	1,78108
NO01	0,97446	1,01046	1,25037
NO02	1,12380	0,97881	1,65443
NO03	0,94034	1,02144	0,59734
NO04	1,02036	0,99594	1,19891
NO05	1,02213	0,99583	0,82645
NO06	1,12578	0,96826	3,24273
NO07	0,96791	1,01317	1,60298
PL21	0,98020	1,00814	1,65303
PL22	0,94092	1,02685	1,75145
PL41	1,02777	0,98935	1,82380
PL42	0,92085	1,03304	1,24006
PL43	1,01128	0,99636	1,66353
PL51	1,04679	0,97715	1,40803
PL52	1,04517	0,98642	1,78350
PL61	1,03938	0,98606	1,20464
PL62	0,97820	1,00964	1,52966
PL63	1,07999	0,96881	1,19586
PL71	1,00930	0,99826	1,27634
PL72	0,96240	1,01468	1,59061
PL81	0,99052	1,00626	1,54794
PL82	1,04822	0,98289	1,30632
PL84	0,99409	1,00633	1,59974
PL91	0,95135	1,02404	1,55989
PL92	0,97941	1,00991	2,01906

NUTS 2	SI High & Medium dig-skill	SI Low & Non-dig skill	SI CCO
EL63	0,99340	1,00701	0,63104
EL64	0,97510	1,01118	0,62870
EL65	1,00915	1,00178	0,70562
ES11	1,01143	0,99852	1,28937
ES12	0,95514	1,01815	1,47443
ES13	0,99532	1,00328	1,14808
ES21	1,03757	0,98283	1,34402
ES22	0,94431	1,02351	1,26564
ES23	0,96816	1,01321	1,20688
ES24	0,99669	1,00225	1,20831
ES30	1,02721	0,97953	1,22910
ES41	1,00811	1,00086	1,15363
ES42	1,01870	0,99782	1,28085
ES43	1,11617	0,97247	1,56700
ES51	1,06253	0,97315	1,33212
ES52	1,07481	0,97714	1,43251
ES53	1,12104	0,95978	1,36356
ES61	1,03613	0,98999	1,12642
ES62	1,06201	0,98451	1,42270
ES63	1,13580	0,93871	1,53736
ES64	0,97238	1,01155	0,51245
ES70	1,06532	0,97851	1,19429
FI19	1,00297	0,99863	1,40803
FI1B	0,95827	1,02095	1,36157
FI1C	1,08402	0,96941	1,55440
FI1D	1,05998	0,98222	1,27744
FI20	1,13182	0,95649	1,14402
FR10	1,02859	0,97617	0,30655

NUTS 2	SI High & Medium dig-skill	SI Low & Non-dig skill	SI CCO
PT11	1,05906	0,97733	0,64291
PT15	1,08717	0,97030	0,85275
PT16	1,03416	0,99158	0,66949
PT17	1,00944	0,98806	0,66733
PT18	1,13977	0,96150	0,66001
PT20	1,08815	0,97121	0,85405
PT30	1,13544	0,96090	0,77390
RO11	0,96240	1,01479	0,88336
RO12	0,91101	1,03607	1,17335
RO21	1,14154	0,98389	1,17335
RO22	0,98610	1,00844	1,13128
RO31	0,99041	1,00743	1,22437
RO32	0,98906	1,00232	0,97523
RO41	1,12185	0,98060	1,36211
RO42	0,98047	1,00973	1,42952
SE11	1,02509	0,97973	1,06357
SE12	1,04153	0,98278	1,08768
SE21	1,04975	0,98594	1,13668
SE22	1,00965	0,99589	1,09167
SE23	1,00623	0,99608	1,12746
SE31	0,95276	1,01841	0,99723
SE32	0,95367	1,01871	0,92922
SE33	0,92100	1,03055	0,91859
SK01	0,98329	1,00451	1,20588
SK02	0,95536	1,01799	1,14442
SK03	1,01016	0,99764	1,52129
SK04	1,06818	0,98109	1,40048

Source: Authors’ elaboration.

Appendix D: Sensitivity Index (SI) score for digital and non-digital trademark classes

The sensitivity index (SI) during the pandemic was calculated using the 2020-2021 average in relation to 2018-1019. We calculated it using the number of trademark classes, separating them by digital and non-digital by region in relation to the European Union average in the same period.

Table 6 - Sensitivity Index (SI) scores for regions by type of trademark classes (digital and non-digital)

NUTS 2	SI Non-digital trademark classes	SI Digital trademark classes
AT11	0,92091	0,96329
AT12	1,13619	1,04642
AT13	1,08182	1,00265
AT21	1,12330	0,85177
AT22	0,84753	0,71250
AT31	1,10556	0,96007
AT32	1,10273	1,05999
AT33	1,20512	1,31473
AT34	1,06931	0,91807
BE10	1,04871	0,93640
BE21	0,92753	0,91849
BE22	0,98792	1,06607
BE23	1,08017	1,11032
BE24	1,26015	0,92527
BE25	1,13422	0,86712
BE31	1,15705	0,92119
BE32	1,13505	1,38395
BE33	0,92422	1,07362
BE34	0,74389	0,80961
BE35	0,93064	1,28733
BG31	1,49196	1,67705
BG32	0,96012	1,00238
BG33	1,24398	1,13879
BG34	0,95651	0,87314
BG41	1,22277	1,38250
BG42	1,20404	1,38790
CH01	0,92678	0,94347
CH02	1,09499	0,79471
CH03	0,91693	1,13242
CH04	0,91695	0,74263
CH05	0,98887	1,02730
CH06	0,80743	0,82582
CH07	0,72603	0,75825
CY00	1,04432	1,52608
CZ01	1,49736	1,05636
CZ02	0,73750	1,11644
CZ03	1,38829	1,13088
CZ04	1,58476	1,51064
CZ05	1,40910	0,87901
CZ06	1,11494	1,64825
CZ07	1,53473	1,05985

NUTS 2	SI Non-digital trademark classes	SI Digital trademark classes
FRE1	0,70888	0,75535
FRE2	1,30616	1,45762
FRF1	0,68483	0,81583
FRF2	0,98546	1,20460
FRF3	1,23138	1,07531
FRG0	1,04502	1,08686
FRH0	0,80920	0,96298
FRI1	0,92836	0,90361
FRI2	0,50764	0,40536
FRI3	0,86852	0,89203
FRJ1	0,99344	0,97429
FRJ2	0,96847	0,85172
FRK1	0,83880	0,90026
FRK2	0,98214	0,79496
FRL0	0,87844	0,97543
FRM0	1,35585	2,01877
FRY1	0,44698	0,33646
FRY2	2,58258	0,33045
FRY3	0,00000	1,23369
FRY4	0,74497	0,00000
HR03	1,45840	1,99774
HR04	1,61247	1,47627
HU11	0,95927	1,23294
HU12	1,11136	1,03241
HU21	1,27755	1,79913
HU22	0,98384	1,41225
HU23	0,63097	2,77581
HU31	1,31565	1,44573
HU32	1,62756	2,08186
HU33	2,60994	1,99289
IE04	1,42472	1,48946
IE05	0,85578	1,10245
IE06	0,95089	1,01974
IS00	0,58618	0,44862
ITC1	1,04024	1,17762
ITC2	1,56799	1,63701
ITC3	0,69922	1,08549
ITC4	0,94225	0,97804
ITF1	1,00269	1,43931
ITF2	0,61918	1,54212
ITF3	0,86245	1,08952

NUTS 2	SI Non-digital trademark classes	SI Digital trademark classes
CZ08	0,96847	1,70444
DE11	1,07960	1,06119
DE12	1,07163	1,06938
DE13	0,77104	1,05619
DE14	0,97942	1,07103
DE21	1,11579	1,07705
DE22	1,32862	1,45570
DE23	0,95328	0,98496
DE24	1,02213	0,86304
DE25	1,00134	0,88067
DE26	1,31642	1,04573
DE27	1,41737	1,22404
DE30	1,21274	1,11618
DE40	1,14192	0,94335
DE50	0,99738	1,18963
DE60	1,25834	1,19602
DE71	1,16973	1,08967
DE72	1,20478	0,87871
DE73	1,30382	1,09678
DE80	0,98000	0,81147
DE91	1,34109	0,92527
DE92	0,96903	0,82246
DE93	0,77671	0,82000
DE94	1,00948	1,16226
DEA1	1,09626	1,20150
DEA2	1,09519	1,00521
DEA3	0,88423	1,21865
DEA4	0,91211	1,22103
DEA5	1,01245	0,97672
DEB1	1,06852	1,17991
DEB2	1,02318	0,78540
DEB3	0,96929	1,21224
DEC0	0,94612	1,27561
DED2	1,61249	1,59731
DED4	0,95888	1,26482
DED5	1,15005	1,22769
DEE0	0,75983	0,78422
DEF0	1,05632	0,96338
DEG0	1,29727	1,11577
DK01	0,95856	1,00858
DK02	0,77237	0,92067
DK03	1,15807	0,99165
DK04	1,08162	1,13431
DK05	0,84372	0,94289
EE00	1,07830	1,22250
EL30	1,47576	1,12326
EL41	0,81947	0,92527
EL42	3,87387	0,39654
EL43	0,77625	0,90026
EL51	2,76013	3,93239
EL52	1,08794	1,00493

NUTS 2	SI Non-digital trademark classes	SI Digital trademark classes
ITF4	1,27203	1,38228
ITF5	2,17171	1,17762
ITF6	1,11783	1,33808
ITG1	1,33482	1,42600
ITG2	1,39683	1,79502
ITH1	1,11433	1,18085
ITH2	1,36279	1,17550
ITH3	1,11340	1,10423
ITH4	0,91720	1,28902
ITH5	0,92753	0,99481
ITI1	1,11360	1,11721
ITI2	1,07162	1,28188
ITI3	1,00186	1,21175
ITI4	1,04340	1,14998
LI00	1,19883	1,05073
LT01	1,29084	1,37350
LT02	1,84860	2,20302
LU00	0,87519	0,75596
LV00	0,96661	1,15016
MT00	0,95870	0,91816
NL11	1,09327	0,90270
NL12	1,10091	1,27855
NL13	0,99938	1,30487
NL21	1,20260	1,24845
NL22	0,95510	0,79144
NL23	0,70490	0,79471
NL31	0,94083	0,92371
NL32	1,04983	1,13021
NL33	1,03622	1,14773
NL34	0,81439	1,05378
NL41	1,12611	0,93147
NL42	1,18668	0,50673
NO01	0,99618	0,66153
NO02	3,30159	3,70108
NO03	0,80004	1,12533
NO04	1,25460	1,10518
NO05	0,81947	1,20123
NO06	1,24918	2,60758
NO07	0,69176	1,09876
PL21	1,50331	1,37493
PL22	0,88696	1,04848
PL41	1,41709	1,60096
PL42	1,24056	1,06363
PL43	0,70292	1,39407
PL51	1,25269	1,22592
PL52	1,57210	0,95912
PL61	0,95263	1,22171
PL62	1,63494	1,78114
PL63	1,04980	1,23061
PL71	0,82992	1,05565
PL72	1,34743	0,58332

NUTS 2	SI Non-digital trademark classes	SI Digital trademark classes
EL53	0,48423	0,00000
EL54	0,51652	2,05615
EL61	1,32621	1,37493
EL62	0,74836	1,85054
EL63	1,10682	1,33007
EL64	1,02227	1,54212
EL65	1,13544	2,08186
ES11	1,04471	0,87712
ES12	1,14903	1,22237
ES13	0,54135	0,44790
ES21	1,02528	0,86054
ES22	0,69146	0,88801
ES23	0,96342	0,94679
ES24	0,70663	0,63326
ES30	0,94143	0,97700
ES41	0,91946	0,82246
ES42	0,82320	0,69395
ES43	0,99418	0,47709
ES51	0,95139	0,91552
ES52	0,83374	0,99822
ES53	0,74497	0,71762
ES61	0,91488	0,97087
ES62	0,94472	0,86444
ES64	0,00000	0,46263
ES70	0,96290	1,01591
FI19	1,23959	1,17658
FI1B	0,96558	1,04183
FI1C	0,90183	0,99558
FI1D	0,86941	0,86202
FR10	0,82944	0,78320
FRB0	0,54419	0,64346
FRC1	0,75492	1,04816
FRC2	1,44069	0,92527
FRD1	0,73164	0,78227
FRD2	0,79154	0,84051

NUTS 2	SI Non-digital trademark classes	SI Digital trademark classes
PL81	1,26483	1,67309
PL82	0,80798	1,43844
PL84	2,23257	2,91121
PL91	1,12623	1,01598
PL92	0,94353	1,22536
PT11	1,12490	1,35630
PT15	0,78636	0,55076
PT16	1,04830	1,09144
PT17	0,95069	1,06483
PT18	0,63938	1,15323
PT20	1,93693	2,03559
PT30	0,87081	0,68598
RO11	1,30726	1,20088
RO12	0,94977	1,27653
RO21	1,21679	1,11032
RO22	2,49291	1,40283
RO31	0,54605	0,66402
RO32	1,47576	1,15381
RO41	0,76908	1,61065
RO42	0,94801	1,12533
SE11	1,11618	1,08235
SE12	1,37210	1,32105
SE21	1,23418	1,05415
SE22	1,28135	1,15174
SE23	0,98517	1,02033
SE31	0,74017	0,63847
SE32	1,08201	0,71554
SE33	0,87313	1,12398
SI03	1,34796	1,36392
SI04	1,24540	0,99308
SK01	1,12726	0,95632
SK02	1,14365	1,39179
SK03	1,26247	1,19741
SK04	1,70151	2,07260

Source: Authors' elaboration.